SMT goes ABMS: Developing Strategic Management Theory using Agent-Based Modelling and Simulation.

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I declare that this thesis, which I submit for the degree of Doctor of Philosophy at the University of Durham is my own work and is not substantially the same as any which has previously been submitted for a degree at this or any other university.

Abstract

For the emerging complexity theory of strategy (CTS), organizations are complex adaptive systems able to co-evolve with their dynamic environments through interaction and response, rather than purely analysis and planning. A promising approach within the CTS context, is to focus on a strategic logic of opportunity pursuit, one in which the distributed decision-makers behave audaciously despite unpredictable, unstable environments. Although there is only emergent support for it, intriguingly organizations can perform better when these decision-makers 'throw caution to the wind' even at their own possible expense. Since traditional research methods have had difficulty showing how this can work over time, this research adopts a complementary method, agent-based modelling and simulation (ABMS), to examine this phenomenon. The simulation model developed here, CTS-SIM, is based on quite simple constructs, but it introduces a rich and novel externally driven environment and represents individual decision-makers as having autonomous perceptions but constrainable decision-making freedom. Its primary contribution is the illumination of core dynamics and causal mechanisms in the opportunity-transitioning process. During model construction the apparently simple concept of opportunity-transitioning turns out to be complex, and the apparently complex integration of exogenous and endogenous environments with all three views of opportunity pursuit in the entrepreneurship literature, turns out to be relatively simple. Simulation outcomes using NetLogo contribute to CTS by confirming the positive effects on agent performance of opportunistic transitioning among opportunities in highly dynamic environments. The simulations also reveal tensions among some of the chosen variables and tipping points in emergent behaviours, point to areas where theoretical clarity is currently lacking, provoke some interesting questions and open up useful avenues for future research and data collection using other methods and models. Guidance through numerous stylized facts, flexible methods, careful documentation and description are all intended to inspire interest and facilitate critical discussion and ongoing scientific work.

Keywords: agent-based simulation; complex, adaptive systems; opportunity; strategic decision-making.

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I was inspired by the millions of agents that played a part in this research process.

This is for the quick and the fearless.

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1. INTRODUCTION

The principles of complexity are penetrating strategic management literature (Cunha and Cunha, 2006). The focal theory for this research is the emerging complexity theory of strategy (CTS). As a simple, but important theory aimed at explaining successful strategy in highly dynamic markets, CTS propositions are considered likely to be correct but have only “rough underlying theoretical logic” (Cunha and Cunha, 2006; Davis, Eisenhardt and Bingham, 2007, p. 484).

This research addresses two important related challenges that face CTS researchers. One is to embrace and integrate contributions from outside strategy, both from the complexity literature and the entrepreneurship literature. The other is to address the difficulty that most research methods have in dealing with uncertainty and the effects of complexity as they unfold over time.

For CTS researchers, organizations are complex adaptive systems able to co-evolve with their dynamic environments through interaction and response, rather than purely analysis and planning. A promising approach, within this context, is to focus on a strategic logic of opportunity pursuit. Distributed decision-makers, faced with choices among perceived opportunities and threats, have been observed to behave enterprisingly despite their uncertainty in a dynamic, unstable, unpredictable environment (Dess and Beard, 1984; Chakravarthy, 1997; Eisenhardt and Sull, 2001; Cunha and Cunha, 2006). However, a most intriguing question in the CTS context remains largely unanswered: *How does such opportunistic behaviour in these environments, which is likely to produce unreliable outcomes for the decision-makers themselves, benefit the organization as a whole?*

Research dating back to Emery and Trist (1965) has pointed to tensions among the drivers of environmental dynamism that are capable of both supporting and undermining environmental munificence. These tensions can cause a dilemma for decision-makers whose entrepreneurial behaviour can be instrumental to organizational success, but also expose the organization to uncertainty and vulnerability (Eisenhardt and Sull, 2001; Green, Covin and Slevin, 2008). Research that examines and can illuminate some of the core processes of opportunity pursuit and the relationship between opportunistic behaviour and organizational performance in highly dynamic environments is important to those organizations, as it can affect how they structure themselves and how they screen and incentivize their people.

Although CTS researchers are aware of the importance of a more precise understanding of the dynamics of opportunity-based strategy, most research methods have had difficulty showing how such inaccessible, complex processes can work over time. To address this problem, this research therefore adopts a complementary method, Agent-Based Modelling and Simulation (ABMS), in line with general calls from researchers for the use of complementary approaches (Balogun, Huff and Johnson, 2003; Geller, 2005; Davis et al, 2007).

The broad aim of ABMS is to place agents (software programs) into a computational framework in which they interact among themselves and with their environment, and to leave the computer to build up the complexity of the whole, from the bottom up (Gilbert and Troitzsch, 1999; North and Macal, 2007; Tesfatsion, 2008). Agents can represent the behaviour of all sorts of entities, in this case the decision-makers.

Scientists using ABMS, like all scientists who model, do not aim to produce perfect models. The simulation model developed in this research, and referred to as CTS-SIM, is based on quite simple constructs. It is the result of a more integrative approach to time and flows than that traditionally adopted. It embraces uncertainty (rather than attempting to reduce it) and incorporates enough detail for an interesting and useful representation of a CTS-type system. The model also possesses a number of important 'observed' system characteristics that can facilitate and guide focussed, critical discussion with a view to evaluating its worthiness to scientists within the user community (von Glasersfeld, 1987; Ahrweiler and Gilbert, 2005).

ABMS shows strong potential for meeting both of the challenges faced by CTS researchers – the need to embrace contributions from outside strategy and to address uncertainty and the effects of complexity as they unfold over time – and therefore provides a promising alternative approach for researching the problem at hand. Consequently, this research joins those researchers gearing themselves for a post-normal, more effective experimental science.

1.1 Context and theory

This section contains a brief overview of the status of strategic management research and then of CTS – its nature, focus and shortcomings. Since this research is about CTS and modelling, this provides the backdrop to the research aims and questions that follow in the next section.

Strategic decision-making

There have been shifts in the strategic management literature following the realization that organizational environments are highly interconnected and in perpetual disequilibrium (Schumpeter, 1942; Emery and Trist, 1965) and populated by heterogeneous, sub-rational 'satisficers' (March and Olsen, 1976; Tversky and Kahnemann, 1986). These have been accompanied by the recognition that organizations are open, interactive and interdependent, consist of large numbers of components and thereby cause uncertainty and undermine prediction (Thompson, 1967; Simon, 1966; Anderson, 1999).

In these environments, a growing body of research has begun to recognize the limited value of uncertainty reduction, asset protection and position-based strategies (Eisenhardt and Sull, 2001; Grant, 2003; McKelvey, 2004). A way of addressing this is understood to be by learning and experimenting, responding and adapting, and minimizing the role of planning and the use of predictive rationality (Axelrod and Cohen, 1999a; Eisenhardt and Sull, 2001; Grant, 2003). For some time, rapid change, coupled with the alertness and drive of decision-makers, has been known to facilitate the discovery and creation of opportunities, often shorter-lived but abundant (von Mises, 1966; Hayek, 1967a; Kirzner, 1997). More recently, strategic goals have been noted to shift from the achievement of sustained to include temporary competitive advantage, and performance goals from profitability and long-term dominance to include growth (Rindova and Kotha, 2001; Eisenhardt and Sull, 2001).

These environmental and behavioural shifts are challenging to understand and can be difficult to model. Some recent research efforts are distinguishable by their shared approach to time, flows and coupling (Farjoun, 2002). Time is perceived as continuous-discontinuous rather than discrete or once-off, flows are perceived as more interactive and no longer implied or absent, and coupling is integrative rather than fragmented (Schendel, 1994; Mintzberg, 1994b; Farjoun, 2002; Crossan, Cunha, Vera and Cunha, 2005). These are recent, ongoing shifts, away from disconnected, mechanistic, neoclassical leanings to more integrated, organic thought, with attempts to embrace rather than subdue uncertainty and complexity.

Linked to these developments has been the recognition that markets are in perpetual disequilibrium due to the dynamics of error, surprise and an abundance of opportunities (von Mises, 1966; Hayek, 1967a; Kirzner, 1997). These drivers motivate a synthesis of strategic decision-making and entrepreneurial thought and theories of complexity, at these points.

Here, where environments are open and organizations are populated by many individual decision-makers, the features of complex systems are plainly evident (Axelrod, 1997; McKelvey, 1999).

Complexity theory of strategy, CTS

CTS does not challenge other theories of strategy that focus on positioning and resources, at least not for their merits in stable markets. Instead, it offers insights specifically for CTS contexts i.e. where time is compressed and environments are dynamic.

Developing theories of strategy in the context of entrepreneurial decision-makers and of principles of complexity, and attempting to synthesize elements of the planning and learning approaches, has given rise to an emergent theory, CTS. CTS draws on powerful streams of literature that go beyond the field of strategic management, including attempts to build on research by the Austrian school of economists into market dynamism and on contributions from the complexity sciences (Cunha and Cunha, 2006; Davis et al, 2007).

Although ‘complexity’ is more of an approach to conceptualizing and modelling open, dynamic systems than being a theory, it offers useful, basic principles that can be applied to organizations (Anderson, 1999; Stengers, 2004; McKelvey, 2004). Complex, adaptive systems (CAS) are open systems that consist of many parts interacting in dynamic, nonlinear fashion, and where memory and intelligence reside throughout the system (Weick, 1969; March, 1994; Brown and Eisenhardt, 1998). These features facilitate path-dependent, adaptive self-organizing behaviour that is emergent and nondeterministic. It is not always possible to predict the behaviour of CAS from an inspection of the parts. Organizations are unmistakeably CAS.

CTS differentiates itself from other management theories by focusing on the importance of time and timing in the pursuit of evolving, temporary competitive advantages in fast-changing, turbulent and uncertain environments (D’Aveni, 1994; Rindova and Kotha, 2001; Eisenhardt and Sull, 2001). Decision-makers, if sufficiently alert and driven, can perform successfully by orienting themselves to the exploitation of opportunities, provided they resign themselves to the likelihood of temporary advantages, error and surprise (Hayek, 1949; Perry, 1991; Koppl and Minniti, 2003). CTS points to changes in the nature of dynamic capabilities, from detailed routines based on past behaviours to flexible, simple rules for capturing fleeting opportunities (Weick, 1995; Teece, Pisano and Shuen, 1997; Eisenhardt and Sull, 2001). It associates successful performance with minimally structured, distributed decision-making (Hayek, 1967a; Prigogine and Stengers, 1984; Anderson, 1999). It is here that CTS draws so deeply on contributions from other fields.

So the task strategic decision-makers have in accounting for the unpredictability of open, nonlinear systems is not to place emphasis on prediction and control but rather, in the mould of CTS, to establish and modify the direction and boundaries within which effective, improvised, self-organized solutions can evolve (Brown and Eisenhardt, 1997; Weick, 1995; Miner, Bassoff and Moorman, 2001). Temporary advantages emerge from local decision-making and interaction. This is both enabled and constrained at the upper organizational level (Simon, 1966; Burgelman, 1983). Decision-making freedom, with just a few guiding or governing rules, is enough to facilitate quick response to change (Brown and Eisenhardt, 1997; Weick, 1995; Eisenhardt and Sull, 2001).

The recipe for success is considered to be a synthesis of strategic intention, managerial foresight and organizational control, and a balance of freedom and constraint (Meyer, Frost and Weick, 1995; Anderson, 1999; Cunha and Cunha, 2006). A minimally structured organization generates novelty by ceaselessly recombining its portfolios or opportunities (Teece, 1997; Rindova and Kotha, 2001; Mayer, 2006). As such, CTS can be regarded as a sort of guerrilla warfare, characterized by opportunism, speed and rapid loss cutting. Success is about networking, placing bets and moving early, rather than key customers and strategic focus (Eisenhardt and Brown, 1998).

Gaps in the literature and caveats

In spite of its strong roots, CTS possesses features typical of simple theory. Although some of the basic processes are known, there is still only a vague understanding of the complexity of the interactions (Cunha and Cunha, 2006; Davis et al, 2007). It builds on novel concepts and hence its articulation needs further research.

CTS is not yet well-established for a number of reasons. One is due to a conceptually imprecise and often implicit treatment of time (Bluedorn and Denhardt, 1988; Butler, 1995; Leybourne, 2006). A result has been an increase in calls for scholars and practitioners to pay closer attention to the role of time, especially since timing, speed and vigilance can affect successful performance in highly dynamic markets (Eisenhardt and Sull, 2001; Cunha and Cunha, 2006; Leybourne, 2006).

Another reason why CTS is still underdeveloped is due to largely stable and predictable environmental representation (Schoemaker, 1993; D'Aveni, 1994; Brown and Eisenhardt, 1998). A result is recognition of the need for a consistent, integrated conceptualization of highly dynamic environments.

A third reason is due to an incomplete understanding of the roles of entrepreneurial decision-makers and their behaviours (Acs and Audretsch, 2003; Mezias and Starbuck, 2003), and hence recognition of the need to attend to the capture rather than reduction of environmental uncertainty (McKelvey, 2004). A fourth relates to the need to answer the call for the conceptualization of markets as made up of opportunity flows and change (Shane and Venkataraman, 2000). A fifth reason why CTS is still underdeveloped, given its focus on an opportunity-based strategic logic, is an unanswered call for integration of the creation, discovery and allocation views of opportunity pursuit (Sarasvathy, Dew, Velamuri and Venkataraman, 2003).

There is a strong stream of literature related to entrepreneurial behaviour, which centres on alertness and the seizing of opportunities (Hayek, 1949; Kirzner, 1997 and others). Nevertheless, *how* these behaviours succeed over time in uncertain, dynamic, noisy, environments has not been fully explained. One reason is because behaviours and relationships among variables are difficult to observe in CAS.

The price is one of vagueness. Increased performance has been associated with increased environmental dynamism due to a high flow of opportunities into the environment (Davis et al, 2007). Yet, despite the flow of opportunities, such environments are capable of being very unattractive (Eisenhardt and Sull, 2001). There is focus on the role of growth and hence faster opportunity seizure than abandonment (Brown and Eisenhardt, 1997; Eisenhardt and Sull, 2001). Yet organizations are expected to move with their environments. There is emphasis on environmental unpredictability, but neglect of the role of surprise (Cunha and Cunha, 2006). Much attention has been paid to alertness and opportunity seizure (e.g. von Mises, 1966; Kirzner, 1997; Eisenhardt and Sull, 2001), but little to opportunity abandonment.

These shortcomings expose the need for an improved understanding of the terms and concepts used to describe the drivers of such environments and the behaviours of the decision-makers that operate in them. It is not easy to address this by purely text-based research. Other tools and techniques that address crucial attributes of CTS systems can add clarity by offering support using a different method, by embracing rather than reducing uncertainty, and by squeezing out ambiguities. When left unresolved, ideas and concepts are not easily shared and the interactions of researchers, who are aware of these deficits, have been likened to ships passing in the night.

Within the framework of these challenges nestles the central and intriguing question of this research: *How do distributed decision-makers benefit the organization in highly dynamic and unpredictable environments by behaving boldly, by 'throwing caution to the wind', at their own possible expense?*

Eisenhardt and Sull (2001, p. 108) have suggested that the "greatest opportunities for competitive advantage lie in market confusion, so [decision-makers] jump into chaotic markets, probe for opportunities, build on successful forays, and shift flexibly among opportunities as circumstances dictate." There is further recent support for attributing success to proactive and reactive behaviour and to risk-taking, rather than to the environment. Although such behaviour is 'fraught with strategic missteps' due to actions that take organizations into new business domains and can place them in "potentially highly uncertain and vulnerable positions", the expectation is that success is internally, rather than externally, driven (Green et al, 2008).

In trying to model these phenomena, or aspects of them, researchers have pointed the way forward for some time. First, to the extent that decision-makers do not always act rationally, have limited attention and cannot sense-make, a model that sufficiently separates process from outcome is required (March and Simon, 1958; March and Olsen 1976; Weick, 1995; Gifford, 2003). Second, if the locus of opportunity discovery or creation lies with people, then cognitive psychology (e.g. insights about intentions, perceptions, issue categorization) is relevant to modelling the process (Dutton and Jackson, 1987; Salgado, Starbuck and Mezias in Augier and March, 2002; Krueger in Acs and Audretsch, 2003).

Third, there is a need to model organizations that transform vigilance into action using tools and techniques that address the crucial attributes of CTS systems, and therefore to extend the framework to the heterogeneous, multi-agent case[1] (Siggelkow and Rivkin, 2005; Cunha and Cunha, 2006; Davis et al, 2007). Fourth, given that uncertainty and unpredictability preclude expectation, error and surprise need to be treated as features of the opportunity exploitation process, blurring the distinction between environment and individual (March and Olsen, 1976; Shane and Venkataraman, 2000).

1.2 Research aims, methods and expectations

Given the many interactive elements of CAS, it is difficult to observe, understand and explain their causes and effects. One might expect there to be tensions among the elements. In the case of organizations operating in CTS environments, these are likely to be between the drivers of the exogenous environment and between the opportunistic behaviours of the individual decision-makers. These are the so-called system inputs. Such tensions can cause unexpected behaviour, tipping points or steep thresholds in the dynamism and munificence

[1] As indicated, the term 'agent' refers to computer software used to represent a decision-maker in an organization. Agents can be used to represent all types of entities – cars, ants, people etc.

of the environment and in the performance of the organization – the aggregate system outputs.

The main aim of this research is *to illuminate and explain how enterprising, opportunistic transitioning among opportunities at the managerial level, that may not be self-serving in dynamic environments, can benefit the organization as a whole.* To achieve this there is a need to examine some of the core dynamics and causal mechanisms of the opportunity-transitioning process. This involves investigating probable causal mechanisms between some of the interactive elements: between the micro-level inputs and macro-level outputs of the system.

Achieving this aim therefore requires that two subsidiary goals be set: a) to examine causal mechanisms between the drivers of highly dynamic environments and their emergent, aggregate behaviour, and b) to examine the relationships between the most significant opportunity-based decision-making behaviours and organizational performance, in such environments.

A necessary condition for this is to observe the system in action. The difficulty with studying an unpredictable system in operation is that, despite being difficult to access, it must be observed often enough at a certain level and over time. This leaves few options for research of this nature. One is to attempt to *capture* artificially the relevant and significant micro-level behaviours that can generate the aggregate behaviours of interest as time unfolds, and to do so often enough for patterns to emerge for observation.

Exploring and testing relationships between variables that produce tensions and nonlinearities is regarded by a growing number of researchers as predestined for an experimental approach using modelling and simulation (Gilbert and Troitzsch, 1999: McKelvey, 2004; Davis et al, 2007). Simulations treat time explicitly, by establishing regular occasions for agents (representing decision-makers) to reassess their actions (Gersick, 1994; Brown and Eisenhardt, 1997). They are particularly useful, arguably necessary, when empirical data is unavailable or inaccessible (Ahrweiler and Gilbert, 2005; Davis et al, 2007), and when there is a need to study the phenomenon over extended time periods that would be difficult to observe with empirical data (March, 1994; Zott, 2003).

Davis et al (2007, p. 481): “simulation is especially useful in the ‘sweet spot’ between theory-creating research... and theory-testing research”. These researchers state that simulation “enables the elaboration of rough, basic (or what we term simple) theory... particularly useful when the theoretical focus is longitudinal, nonlinear, or processual, or when empirical data are challenging to obtain”. They suggest simulation is especially useful when the focus of interest is on squeezing out lack of precision and exposing the underlying complexity of the system, the interim states and emergent behaviours of the organization.

An interesting and useful way of doing this, and an increasingly popular method among simulation scientists, is to capture the simpler, micro-level behaviours using agents, and to allow the complex, aggregate behaviours of the system to emerge, from the bottom up. This restricts the task to carefully defining and quantifying the micro-level rules and variables, and leaves the rest to the power of computer technology. As such ABMS is often used as a test bench for terms and definitions and as a way of implementing aspects of components and systems previously believed impractical.

Because generating data for observation differs from the normal methods of induction or deduction it is now considered by many to be a 'third way' of doing science (Axelrod and Testfatsion, 2008). Attempting to capture change and uncertainty is considered by a number of researchers to be more useful when variables can be controlled and manipulated using computers (Casti, 1997; McKelvey, 2004; North and Macal, 2007). The amount of data generated when studying CAS simply becomes unwieldy for alternative methods.

The arguments for computer simulation are not for the replacement of other methods. They are for complimentary, broader, more flexible methods, and for questioning often taken-for-granted assumptions about how to conduct research. For many researchers its importance for 'effective science' already appears beyond question, for some there is probably no other way of modelling complex systems (Casti[2], 1997; Epstein and Axtell, 1996; Gilbert and Troitzsch, 1999; McKelvey, 2004).

It makes sense to attempt to model organizations this way, particularly CTS-type organizations, even if they are unpredictable, because ranges, boundaries, paths and patterns are identifiable. This can be a source of useful information to researchers and decision-makers (Gilbert and Troitzsch, 1999; Davis et al, 2007; North and Macal, 2007). Conceptualizing markets as made up of opportunity flows and change, suggests that these drivers shape environmental behaviour – dynamism, unpredictability, munificence and so on. Operationalizing these drivers in a computational framework in a sufficiently simple and understandable way can lay a foundation for useful ongoing experimentation.

For uncertain, complex systems there is no hope or need for a true, veridical model. Instead the goal of construction is a more modest one, that of achieving utility and generating interest among users in the community (von Glasersfeld, 1987; Bankes, Lempert

[2] Hence Casti's prediction that, in fifty years time, computational experiments will be seen as the primary contribution of the Santa Fe Institute.

and Popper, 2002; Ahrweiler and Gilbert, 2005). The initial aim of this research, therefore, is to establish whether this can be done in such a manner.

This research therefore specifically attempts to answer calls for the conceptualization of CTS environments as consisting of opportunity flows and change. It adopts a bottom-up approach, which enjoys much-favoured status among many simulation scientists investigating organizational dynamics (Parunak, Savit and Riolo, 1998; McKelvey, 2004; North and Macal, 2007). Since this has not been done before in a bottom-up manner with a view to studying strategy in highly dynamic markets, the research sets out initially to construct a rich CTS environment that enables the user to influence its behaviour through manipulation of the drivers of opportunity flow and change. This lays the platform for achieving the first subsidiary goal, that of examining causal mechanisms between the environmental drivers and their emergent, aggregate behaviour.

Once the environment is constructed, in a manner that facilitates the control (or at least influence over) the emergent attributes or behaviours (dynamism and munificence), it is possible to progress to the decision-making agents. Populating the environment with agents lays the foundation for achieving the second subsidiary goal, that of running extensive simulations for observation and insights into complex strategy-performance relationships, where ranges of possible outcomes and contingencies are possible. Here the focus is on possible causal relationships between a few specific opportunity-based behaviours and agent performance, under different environmental conditions.

As with the environment, the condition for inserting decision-making agents into the model is to facilitate understanding and focus discussion. Purpose-built models, however, are challenging to convey in a sufficiently transparent and explicit manner. To aid the process, it is useful to draw on broad, observed characteristics, or ‘empirical regularities’ (Carley, 1996; Dosi, Fagiolo and Roventini, 2006; Windrum, Fagiolo and Moneta, 2007).

The model therefore specifically takes on board a lengthy list of behavioural regularities that have been ‘observed’ to pertain to individuals in organizations operating in highly dynamic markets. It is not necessary (or achievable) to strive for a perfect model, instead it is possible to abstract and approximate much of the target, without preventing the discovery of useful and interesting insights.

A useful and interesting simulation model like CTS-SIM can add clarity to CTS, provide new insights, and act as a much-needed laboratory for ongoing experimentation. The model is therefore the tool for investigating the intriguing question that is the core of this research. ABMS is the choice of method, not because it is a novel technique and can be applied to a new discipline, but for its suitability in addressing a problem that researchers have had difficulty solving, and for facilitating a useful and interesting research agenda, (Robertson, 2003). Davis et al (2007) suggest that research which is driven purely by method can lead to poor research questions, making it difficult to integrate its contribution with the work of other researchers using other methods.

1.3 Research questions

How does distributed, opportunistic agent behaviour in dynamic modelled CTS-type environments (CTS-SIM), which is likely to generate unreliable outcomes for the agents themselves, benefit the agent 'organization' as a whole?

This is the fundamental, intriguing question of this research. CTS environments are unpredictable, unstable environments abundant with fleeting opportunities. If, as has been observed in recent times (Eisenhardt and Sull, 2001; Green et al, 2008), organizations do benefit from more adventurous opportunity-transitioning behaviour, is this exclusive to rapidly changing environments in which opportunities are fleeting? How does opportunism thrive off increased opportunity flows and change? Despite 'observing' its occurrence, CTS researchers have thus far had difficulty demonstrating and explaining this phenomenon given the nonlinear interaction of so many elements in the system.

Conceptualizing the environment as being made up of opportunity flows and change implies that both flows and change play a causal role in environmental dynamism. One would expect flows of opportunities into the environment to contribute to munificence, but since change can destabilize the environment, it is most useful to understand and explain outcomes when the two interact. This can help point to possible boundaries to the efficacy of opportunism in highly dynamic environments, and reveal environmental configurations within the CTS context that support less adventurous behaviour.

Paring 'opportunity-transitioning' down to the simple 'grabbing and letting go' of opportunities might miss what, in practice, are complex dynamics with many interacting variables. ABMS, with its forced transparency and graphic features, can help to further illuminate and explain such dynamics. CTS researchers recognize the importance of a clear understanding of them. In particular, the roles of the environmental drivers and decision-making behaviours in the opportunity-transitioning process are important for the potential they have of placing organizations in potentially highly uncertain and vulnerable positions due to the exploratory nature of the process (Green et al, 2008). They are important because they can influence the nature of major organizational activities like strategic decision-making (Davis et al, 2007).

Toward addressing the central question of how heterogeneous behaviour 'fraught with strategic missteps' is linked to improved agent performance in the CTS context, it is necessary to investigate whether an exogenous organizational environment can be constructed around significant and important 'observed' characteristics of CTS-type environments in a sufficiently simple, but useful and interesting way. This means that the CTS-SIM environment is to consist of a large and diverse set of fleeting opportunities; it is to be driven externally by continuous, stochastic flows of change; and it is to give rise to simultaneous uncertainties, unpredictability and complexities, such as nonlinearities and sensitivity to small shocks.

At the same time, the CTS-SIM environment is to be transparent and explicit enough to facilitate focussed and critical discussion. This is important when the contributions of the model and simulation outcomes are chiefly an issue of how well they facilitate critical discussion and inspire ongoing scientific interest, in line with a 'user community' perspective (Murphy and Rhaume, 1997; Ahrweiler and Gilbert, 2005). In the case of CTS-SIM, evaluating both model and simulation outcomes depends on whether they can be considered 'a fruitful source for theorising and for developing new models' (Ahrweiler and Gilbert, 2005, 4.7). This is far easier to establish when discussion is guided by broad, 'observed' patterns and is not restricted to abstract arguments (Heine, Meyer and Strangfeld, 2005).

In this research, four variables drive a rich CTS-SIM environment, two for the inception and cession of opportunities (transience and frequency), and two for change (speed and direction). Once the environment is constructed (i.e. the variables are defined and quantified), questions are more tightly scoped: *How do the chosen drivers behave?* Specifically, in the first batch of experiments, how do changes in the drivers affect environmental dynamism and munificence? Are there any tensions among the variables, or tipping points in the behaviour of the environment?

Outcomes of the above simulations inform the ongoing experiments. Having studied the causal mechanisms and illuminated the core drivers of the modelled environment, it is possible to progress to the 'organization' of agents interacting within it. The model is extended to include many highly interconnected agents; the agents are to be heterogeneous and sub-rational (i.e. be programmed to form their own individual, imperfect perceptions and to act on them in spite of their limitations); they are able to act ('tackle problems at the local level'), make surprising errors, yet be part of a simply structured organization that can call upon a central authority to constrain and guide it. Despite surprise, error and discontinuity being pervasive components of the modelled system, these features should not prevent success from emerging. Outcomes need to somehow be generated internally and externally driven and be the result of sheer luck.

Again, the extended model, like the environment on which it builds, should be sufficiently transparent and explicit to facilitate the type of critical discussion that enables evaluation of the contribution of the research. As indicated, from a 'user community perspective', the contribution, in terms of intellectual understanding and adding new knowledge is chiefly an issue of how well it fulfils the expectations and fits with the experience of the community that uses it (Ahrweiler and Gilbert, 2005).

Being able to influence the dynamism of the modelled environment based on the outcomes of the first batch of experiments, means it is then possible to pursue the main problem. To these ends, four significant variables for the capture of opportunism are operationalized and tested: agent drive, persistence, initial commitment and perception renewal.

The process of model construction drew out the importance of distinguishing between behaviours that affect different cut-off points for seizure and abandonment. There are cut-off points based on perceived values, akin to reference points or tolerance levels (Tversky and Kahnemann, 1986), and there are also cut-off points based on numbers of qualifying opportunities. How much an agent will change at a time is a reflection of its level of conviction. So there are levels of conviction and levels of tolerance, each playing a role in agent opportunism.

In the main batch of experiments therefore, simulations were run with adventurous agents programmed to adopt high tolerance and conviction levels for opportunity seizure and abandonment in environments with different levels of dynamism. Performance outcomes were then compared with simulation runs when agents were programmed to be less adventurous. Observation and interpretation of these outcomes represent the culmination of efforts to address the main question at the root of this research.

The process of construction and the simulation outcomes of the above experiments necessitated a final batch of simulation runs. These were useful both as a way of testing the sensitivity of the model to important assumptions, and for their potential of opening up avenues for interesting and useful future research.

Both research chapters, the environmental dynamics chapter and the agent opportunism chapter, finish with additional research to support the evaluation of CTS-SIM in the form of model comparison using a concurrently developed model (Davis et al, 2007). The fundamental constructions of the CTS-SIM and Davis et al modelled environments are compared and illuminated, as are certain simulation outcomes, where this is perceived to be possible and useful.

1.4 Overview of research approach and outcomes

The questions asked in this research are typical for ABMS. Addressing them as described, by developing a computer simulation as a test bench for a theoretical organizational framework, has only recently been considered practical. Also typically, developing the model and simulation, CTS-SIM, invoked a willingness to work incrementally from the simple to the complex. This is, in part, a reflection of the tension between two roles that need to be played as researcher, that of the modeller striving for simplicity, and that of the simulation scientist striving for ‘realism’ (Carley, 2002).

Research outline

The research is broken down into six parts (chapters). Following this chapter, a review of the literature helps to establish the context and structure of this research. It draws on contributions from four main areas of academic interest: strategic decision-making in organizations, entrepreneurial behaviour, complexity and agent-based modelling. Because the focus is on CTS, the literature review purposely neglects much of the detail in these fields, and instead scans the landscape with a wider lens.

The literature review begins with an outline of research in the fields of strategic management and entrepreneurship that explicitly converse with the principles of complexity and ABMS. It focuses mainly on historical and conceptual shifts, especially those associated with rapid environmental change, the behavioural limitations of decision-makers, and configuring more dynamic models. It also addresses the newness and dynamism associated with the exploitation of entrepreneurial opportunity, and considers contributions to our understanding of system attributes such as disequilibrium at a point in time and uncertainty as limited attention. The main section that follows is devoted to the contributions of researchers to our understanding of organizations as complex adaptive systems (CAS), and considers the implications of modelling these using ABMS.

Chapter 3 addresses issues of methodology and methods for this research. Discussions of epistemological questions are currently considered open, no particular approach being regarded as binding. However, this does not relieve simulation scientists from the obligation of publishing their epistemological assumptions. The chapter also describes the methods of design and analysis used for this research, assesses their appropriateness, and identifies the main areas in which strength of method is rooted.

Chapters 4 and 5 are devoted to describing the research conducted, from model construction and verification through to the experimentation and model evaluation phases. Both chapters follow the same 'roadmap' (Davis et al, 2007). The first models, and experiments with, the opportunity-based CTS-type environment; the second extends the first, modelling and experimenting with the CTS-type system i.e. including the agents that transition among opportunities. The final chapter contains a brief discussion and summary of the main findings of the research, to the point of reaching conclusions.

Research outcomes

The overall outcome is a new synthesis of thought and experimentation that permits a form of empirical work not previously done. In all, simulation outcomes offer a rich representation of CTS-type environments and deeper insights into the differential impact of opportunity-transitioning behaviours on aggregate agent performance.

Allowing model construction to be guided by numerous stylized facts produced a model which can be challenging to grasp and places high attention demands on the reader. Despite its richness, CTS-SIM focuses on specific issues and remains, throughout the research, directed toward answering the main research question.

The initial phase of construction introduces a simple framework developed for this research, and referred to as the RPX framework. It begins with a 'realistic' externally driven environment (R). It is the platform for further development, which allows for the integration of agents with autonomous, heterogeneous perceptions (P) whose performance (X) is based on the accumulation of payoffs from following an opportunity-based logic of constrainable action.

Construction of the environment also involves the 'unpacking' of the drivers of dynamism and munificence. This opens up a useful and interesting state-space, abstract enough for experimentation. Running extensive simulations over selected regions of the state-space permitted the emergence and observation of patterns in agent strategy-performance relationships that tend not to emerge in CAS from small samples.

Simulations of the modelled environment illuminate the interactive relationship among the causal variables that drive emergent environmental dynamism and munificence. Most important, the model enables the user to change the parameters of the drivers and thereby influence this emergent behaviour. This is a useful outcome for the ongoing research.

Simulation outcomes show that increases in driver levels of opportunity flows and change generally increase environmental dynamism and decrease munificence. These patterns only really reveal themselves at the aggregate level and over time. As expected, at the lower level behaviour is noisy and patterns are easily hidden.

Simulation outcomes reveal the different roles of the drivers of the environment, sensitivities to small changes in the drivers, and to fundamental assumptions about how they interact. Most interesting is the suppression of all aggregate patterns at certain settings due to tensions between the drivers. Even small changes in the settings are enough to send the environment off on a completely different trajectory, which is typical of CAS.

Simulating the environment first pointed to the inadequacy of attributing any efficacy of opportunism in CTS environments purely to an increased flow of opportunities into the environment. Although increased flows do improve environmental munificence in the model, their sensitivity to small changes and the effects of other drivers of flow and change indicate that more is probably required to explain successful performance in such environments.

The interaction of the four chosen drivers of the environment opens up a state-space interesting and large enough to warrant further investigation of its behaviour. The sheer size of the state-space prevented a full investigation of all possible configurations, thereby opening up an interesting agenda for ongoing work and calling for modesty when interpreting the behaviour of such environments. This part of the research results in several propositions for the support and further development of CTS.

The main phase of construction (the extended model) facilitates the integration of R, P and X i.e. integrates the ‘realistic’ externally driven environment and the agents. The RPX framework is also the platform for integration of the three views of opportunity pursuit in the entrepreneurship literature.

As with the environment, important stylized facts also inform the extended model. CTS-SIM agents have limited attention and imperfect perceptions. Since they cannot predict, surprise and error are inherent features of the system. They can nevertheless choose among potential payoffs, bravely or cautiously. They form a ‘flexible constitution’, akin to a single fluid organization. Their freedom to act on their preferred choices, however, can be constrained by a different agent-type which is programmed to represent the leadership of the ‘organization’.

Running extensive simulations using the extended model (in the main batch of experiments) produced further interesting and useful outcomes. Again, emergent performance patterns only revealed themselves over time and after hundreds of simulation runs per parameter setting, serving as further justification for the method used to generate them. Most important, in addressing the main research question, the model demonstrates that distributed opportunistic decision-making by agents representing decision-makers in the ‘organization’ can improve overall performance in the CTS context, in spite of the pervasiveness of error and surprise. This supports observations that CTS, in terms of probing for opportunities and shifting among them, can be successful in spite of the likelihood of ‘strategic missteps’.

Simulation outcomes add strength to suggestions that success is internally driven, while drawing out the need to investigate more thoroughly the bounds on the environmental configurations to which this applies. This research reveals that despite high levels of flow into the modelled environment, slowed change and low transience are enough to induce a less adventurous agent posture.

There is also support for the intuitive argument that the flow of opportunities into highly dynamic environments is a likely contributor to success. Nevertheless, by illuminating the complex core dynamics and sensitivities to small shocks and fundamental assumptions, this research does not support simple explanations.

Part of the complexity relates to the deconstruction of opportunism in the form of increased agent conviction and tolerance levels. These behaviours and postures have different causal effects on agent performance. The research reveals the utility of deconstructing opportunistic behaviour and of differentiating between the effects on performance of faster seizure of new opportunities vis-à-vis slower abandonment of currently exploited ones.

Simulation outcomes also offer clarity in the agent opportunity-transitioning process in other ways. They draw out the distinction between challenges to successful agent performance caused by an unpredictable, dynamic environment and challenges caused by agent limitations. They also draw out the importance to improved agent performance of increased scope of attention over the renewal of perceptions in unpredictable environments.

Finally, simulation outcomes point to a tension between decision-maker opportunism and leadership constraint on decision-making. Lifting constraints on the decision-making agents reveals an emphasis on ‘extreme’ opportunity-transitioning. The model establishes the conditions, and isolates causal mechanisms for the emergence of an opportunity-transitioning curve with a power law signature, thereby opening up an interesting agenda for future research, that of eventually fitting and validating the curve.

In all, these outcomes confirm that a bottom-up approach is particularly useful when trying to understand important aggregate behaviours such as environmental dynamism and organizational performance. They also led to several further propositions for the support and further development of CTS.

The usefulness of a bottom-up approach is underscored by some additional research which aims to further facilitate the evaluation of CTS-SIM. This part of the research uses model comparison. The treatment of opportunity flow into the environment and environmental unpredictability are comparable in the CTS-SIM and the Davis et al models. However, treatment of environmental complexity and ambiguity differs. CTS-SIM allows complexity to emerge from the bottom up, whereas the Davis et al model adopts a top-down approach. CTS-SIM integrates ambiguity with the agents, whereas the Davis et al model treats ambiguity as an environmental dimension. These differences are reconciled, however, and both models produce independent simulation outcomes that make for interesting comparisons.

This research complements the work of others, uses a longitudinal, integrated context and attempts to manage the uncertainties characteristic of strategic decision-making in organizations. In doing so, it answers researchers' calls for an adequate treatment of time, for separation of process from outcome, for recognition of individuality, uncertainty and hence error and surprise as features of the opportunity exploitation process.

The research also answers calls for a consistent, integrated conceptualization of markets as made up of opportunity flows and change, and for the integration of the creation, discovery and allocation views of opportunity pursuit. Most models overlook these issues. Importantly, CTS-SIM takes agent-based simulation a step further by modelling organizational behaviour in terms of autonomous perception formation, but constrainable decision-making autonomy.

Demonstrating and explaining how agent opportunism can improve performance in uncertain, dynamic, noisy, environments over time is important because it can point to how organizations might better structure themselves and screen, motivate and reward their people. Demonstrating and explaining the role of opportunism in CTS environments has proved a difficult task because behavioural patterns are not easy to observe in practice. Insights into the agent opportunity-transitioning process are important because of their potentially close link to strategic decision-making and the potential there is of placing organizations in uncertain and vulnerable positions due to the exploratory nature of the process. They should also be useful and interesting to entrepreneurship researchers, due to calls from that quarter for the integration of the three views of opportunity pursuit.

The primary contribution of the research is the illumination of causal effects and core dynamics associated with the agent opportunity-transitioning process. The research reveals core uncertainties, demonstrates tradeoffs, shows the apparently simple to be complex and complex to be simple, and points to boundaries of application. These go to the root of the research problem.

It is nevertheless best to view the research somewhat independently of its value to CTS. Models are autonomous. CTS-SIM offers directions for data collection, raises interesting new questions and opens up useful avenues for ongoing research, including experimentation using extended versions of the model. It is a useful platform for aggressive experimentation, opening up a way of implementing aspects of CTS systems previously thought impractical.

Although the framework on which CTS-SIM is built and the conceptualization of the exogenous environment are novel, they are responses to calls from other researchers. To this extent, the research is partly method-driven. Model construction is also closely guided by previous scientific observations. It is sensitive to different schools of thought, and steps are taken throughout to ensure that it is explicit, transparent, flexible and accessible. This is to attend to the requirements of users and to inspire and focus critical discussion.

The transparency of CTS-SIM makes it easier to review and analyze. This also helps to draw out its scope and limitations, and point the way to useful avenues of future research, including promising model extensions. For example, there may be deeper micro-level variables than those chosen for this version of the model. Also, the model does not account for the possible effects of group dynamics. It ignores the effects of shifting opportunity-transitioning costs and resource scarcity. Each of these is an opportunity for model extension, further experimentation and potentially interesting insights that can add to model utility.

Reservations have been expressed about unorthodox approaches to research, especially when they are based on complicated ideas and technologies (Binmore, 1998). These are addressed in Chapters 2 and 3. CTS-SIM does have limitations. These relate, in particular, to the reduction of complexity and nonlinearity typical when studying parts of CAS. Although exploring and testing abstractions is one of the main points of science, this calls for modesty when trying to interpret simulation outcomes in this research.

Another limitation relates to the model's over-reliance on system features taken from other research. Comparing the model with other ones is difficult due to its different theoretical goals and content and the current lack of standard techniques for agent-based construction and experimentation. Also, in spite of the benefits associated with one-stop modelling efforts, there are obviously always limits on effort and skills inputs.

Despite these limitations, the importance and usefulness of researching the main problem to other researchers, the advantages of adopting a complementary approach to address it, and the way in which the model and simulation process is described are powerful reasons for considering this research to be a ‘fruitful source for theorising and developing new models’ (Ahrweiler and Gilbert, 2005).

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2. LITERATURE REVIEW

This review has several objectives. They are, following Hart (1998), to establish the context and structure of this research; to distinguish between relevant research conducted to date and future perspectives; to identify the main methodologies and research techniques that have been used in the field; to disclose the variables relevant to the research; and to identify the relationship between the academic ideas presented and business practice.

Klein (2004) cites a number of examples of subject areas that are too complex and in which areas of thought overlap, for anything but an interdisciplinary approach. In bridging the need for a variety of disciplines with a problem-solving orientation, the term 'transdisciplinary' is applied. The problems that decision-makers face are 'wicked and messy' and better approached using a kaleidoscopic[3] than a microscopic approach. By placing this research within the context of a 'post-normal' science, the intention is to shift from past precise, certain estimates to feasible ones when addressing problems that are driven by complex cause-effect relationships (Funtowicz and Ravetz, 1994; Klein, 2004), forcing the need to keep abreast of research both within and beyond the field of management. This is so because such shifts often tend not to be triggered from within.

Following Hart (1998) and Klein (2004), this chapter is divided into three sections. The first section addresses research in the areas of strategic management and entrepreneurship research that specifically converse with issues of complexity and ABMS. The first part discusses historical and conceptual shifts in strategic decision-making models, specifically those associated with rapid environmental change, the behavioural limitations of decision-makers, and configuring more dynamic models.

The second part addresses the newness and dynamism associated with the exploitation of entrepreneurial opportunity. It considers the contributions to our understanding of system attributes such as disequilibrium at a point in time and uncertainty as limited attention, including two well-supported models of opportunity exploitation.

The third part discusses the relevant literatures associated with complexity and ABMS. It traces through the contributions of researchers to our understanding of complex adaptive

[3] Klein attributes this new metaphor to Robert Eisenstein, U.S. National Science Foundation.

systems, CAS, and considers the implications for modelling these. It covers contributions that have roots in other fields of inquiry, exposing the sometimes arcane terms and concepts that are applied, and identifying characteristics commonly associated with CAS. In all, it points to the increasing importance and implications of viewing organizations as CAS, and the progress of researchers towards more effective experimental science.

Section 2.2 considers the emerging complexity theory of strategy, CTS, which is the focus of this research. Building on the previous sections, it identifies the roots and scope of application of CTS, outlines the environment and organization according to CTS, the behaviours of the people that are part of the system, and areas for developing the theory. Section 2.3 finishes with a brief synthesis of the most relevant contributions. This is the platform for Chapter 3.

2.1 Modelling strategy in dynamic environments

This section begins by tracing the shifts from early, static organizational configurations through to more dynamic ones and efforts to understand strategy within the context of interactive and integrated ‘emergent planning’. It specifically follows the shifts that have accompanied developments toward more rapidly changing environments and interconnected populations and, by building on previous contributions rather than breaking with them, arrives at a point where models treat time as incessant rather than discrete, flow as interactive rather than sequential, and the treatment of constructs as integrative rather than independent.

2.1.1 Strategic decision-making

Mechanistic approaches

The main concerns of researchers in the area of strategic decision-making have been to explain what determines organizational performance and to identify what affects organizational strategy. The outcome is one that is “ambiguous, fragmented and to a large extent multi-vocal” (Choo, 2005, p. 104). How it got there is best understood in the approaches researchers have taken in terms of the underlying strategic logic, organizational goals and decision-making environments, competitive advantage, and the link between strategy and performance.

Research in the area of strategy has been impacted by studies of how people make decisions, progressing from a neoclassical view, with decision-makers as rational, utility maximisers[4], to a behavioural view, with organizations populated by sub-rational satisficers (March and Olsen, 1976; Tversky and Kahnemann, 1986). The notion of sub-rationality was an acknowledgement of peoples' limits due to lack of knowledge, computational ability, and ability to consider more than a few factors simultaneously, placing an upper bound on their objective rationality. The notion of satisficing behaviour resulted from this, peoples' preference for solutions they find personally sufficient, rather than optimal. Organizations, strategies and performance[5] came to be recognized as heterogeneous in nature, and information flows often as distorted and misunderstood, with the consequence that modelling them would become more challenging.

Most models of management, in attempting to account for the relationships between strategy and the organization – resources, environment, structure and performance (Miles and Snow, 1978; Porter, 1983; Wernerfelt, 1984) – were influenced by Newtonian mechanics and microeconomic processes. Here Farjoun (2002) identifies the concepts of time, flow and coupling as distinctive i.e.:

1) Time as a discrete, one-off formulation and implementation of choice, rather than as a continuous process, in which learning and history play a role. Based on current environmental conditions, the model moves efficiently toward an equilibrium solution. Most studies use variance models, cross-sectional in design.
2) Flow as sequential and directional (e.g. resource → strategy, environment → strategy → performance), with feedback loops either implied or absent.
3) Coupling (within and between models) as differentiated and fragmented.

Subsequent, and ongoing, research adopted the perspective of strategic processes evolving over time, more interactive and more integrative, thereby extending the above mechanistic, rational, prescriptive models. In fact, Farjoun points out that earlier process orientation including learning and path dependence had been considered (e.g., Selznick, 1957; Chandler, 1962), but were largely neglected thereafter. At any rate, ideas from other disciplines, including both the social and natural sciences, eventually completely exposed their limitations.

[4] This refers i.a. to 'Rational Expectation Theory' or Rational Choice Theory.
[5] This has been challenged by Hamel's 'strategic convergence' (2000), whereby more successful strategists are imitated by competitors with the result that strategic value decays over time.

Organic approaches

In contrast to the stable and predictable model of the environment, attention to dynamic market processes that are less certain has increased (Nelson and Winter, 1982; Dosi et al, 1997). The environment is now viewed as more inclusive and continuous, more interactive and integrated with its constituent parts, Farjoun (2002, p. 574):

> "The environment includes political, economic, social, institutional, informational, technological, and demographic aspects, conditions, and developments... actors' resources, technologies, strategies, relationships and interactions, and performances, and external developments, forces, events, and discontinuities that may affect them and the focal firm... past and current environments, and future environments in which the firm may potentially operate either as a result of its own initiatives or the result of the initiatives of other actors."

In other words, the environment is viewed as a state and a path, integrating the notions of structure and evolution, the behaviours and effects of actors, and as influencing its own path. In environments where plans proved inadequate at times, the concept of emergent strategy, an 'endless stream of actions recognized as pattern after the fact' (Mintzberg and Waters, 1985), seems a viable alternative. The suggestion is that strategy and turbulent environments constantly co-evolve.

Coupled with this approach, models have highlighted process and learning (e.g. McGrath, MacMillan and Venkataraman, 1995; Teece et al, 1997) shifting to an evolutionary focus, and the idea that 'history matters' (Nelson and Winter, 1982; March, 1994; North and Macal, 2007). Such models, rather than opposing the idea of steady states and strategic positions, attempt to explain organizational performance in terms of historical developments, and by observing the pace and path of change (Barnett and Burgelman, 1996). Models of real options (e.g. Bowman and Hurrey, 1993), commitment (Ghemawat, 1991), and dynamic capabilities (Teece et al, 1997) still see strategy as being subject to planning, but highlight its continuous and path-dependent nature.

They examine how initial conditions, timing, managerial choices, decisive moments, learning, and path-dependent processes both enable and constrain current states and in turn provide platforms for future developments (Mitchell, 2004). Some of these models suggest that particular paths may influence outcomes examined at a particular time, but that history does not necessarily work efficiently to produce the optimal configurations and alignments suggested by the mechanistic views.

With the growing appreciation of interaction and interdependence among constructs and variables, feedback loops are being added to improve the mechanistic perspective. Here organizational heterogeneity is the result both of current conditions and historical interactions and interdependencies, endogenous and exogenous (March, 1994). Strategy and performance can be viewed "as an ongoing sequence of capabilities-conditioned adaptations by firms which in turn become exogenous events in the environments of the managers of other firms." (Henderson and Mitchell, 1997, p. 5).

Besides a more incessant approach to time and a more interactive approach to the constructs and variables, a third set of 'organic' developments[6] has been that of integrating the many different concepts and phenomena by recognizing the above interdependencies (Burns and Stalker, 1961; Farjoun, 2002). This provides a more holistic picture (again emulating earlier research, e.g. Chandler, 1962), bridging previously fragmented models with their many disconnected parts, and counteracting the growth of alternative views and approaches.

In all, these assumptions register an epistemological shift from mechanistic to organic, discrete time to incessant, directional to interactive, and differentiated to integrated constructs and models (Farjoun, 2002). The simpler, static, linear assumptions of the mechanistic stream suit a stable, predictable environment (e.g. Pettigrew, 1992), linear (e.g. Henderson and Mitchell, 1997), and fragmented (e.g. Schendel, 1994). But complex, unpredictable, rapidly changing environments exposed their limitations (D'Aveni, 1994; Brown and Eisenhardt, 1998). The single, rational actor is replaced by more complex causal perspectives, the focus shifting away from strategic choice toward change, with attempts to integrate phenomena, concepts and variables to address the 'messy side of reality' (Farjoun, 2002).

Although there is growing appreciation of the complex, interdisciplinary nature of strategy, current developments do not necessarily break with the past, but build on it. Postures, states and plans are necessarily part and parcel of decision-making, to be merged with observation and with incessant, temporal and emergent conditions.

The decision-making framework is hierarchical (Simon, 1966), with the upper levels changing direction less frequently than the lower, but in a dialectical manner, with upper level strategic changes affecting lower level tactics and vice-versa (Burgelman, 1983; Farjoun, 2002). The organization attempts to continually realign itself with its environment

[6] Burns and Stalker (1961) used the terms mechanistic and organic to describe differences between organizational structures and management styles, Farjoun (2002) to describe different concepts and methodological models, both on a continuum.

(Porter, 1995; Thompson, 1967) through goals and actions at all levels, without any guarantee of success.

Models of strategic decision-making involve selectively identifying, influencing and responding to endogenous and exogenous constraints which determine success, at least for a limited time (Pettigrew, 1987; Ghemawat, 1991). Here Cilliers (2000, p. 29) points to the role of decision-maker, or agent, “awareness of the contingency and provisionality of things” in shaping the organization’s passage, of willingness to change perceptions and adapt to them, which he considers preferable to a ‘false sense of security’.

The discussion thus far draws back from the ‘many competing fashions, perspectives and directives’ associated with this area of research, and focuses on key historical and conceptual shifts. It builds on the realization that environments are more rapidly changing, interconnected and populated by heterogeneous, sub-rational satisficers, rather than the traditional utility maximisers. It highlights the shift toward integrated ‘emergent planning’, and arrives at a junction where models, distinguishable by their shared approach to time, flow and coupling, are better perceived as incessant, interactive and integrative than as static, mechanistic configurations.

This landscape is more complete when integrated with the key relevant areas of outside influence that have helped shape it. Doing so is the objective of the rest of this section. The exogenous changes associated with the development of organic approaches to strategic decision-making results in the need for new and ongoing search-and-exploit actions to complement existing actions. This newness and dynamism has been an area of recent focus in the field of entrepreneurship. Acs and Audretsch (2003, p. 6): “Our definition of entrepreneurship embraces all businesses that are new and dynamic regardless of size or line of business, while excluding businesses that are neither new nor dynamic as well as all non-business organizations.”

2.1.2 Entrepreneurial dynamics

This part of the discussion addresses the newness and dynamism associated with the exploitation of entrepreneurial opportunity. It considers the contributions to our understanding of system attributes such as disequilibrium at a point in time and uncertainty as limited attention, including two well-supported models of opportunity exploitation. It also includes issues not exclusively associated with the domain of entrepreneurship, but that nevertheless improve our understanding of the entrepreneurial process and opportunity exploitation.

Again, by zooming out, the intention is to further develop the shape and outline of this research landscape, in line with the more useful ‘kaleidoscopic’ approach. Ignoring these contributions altogether, however, would be to miss its important features. Shane and Venkataraman (2000, p. 219): “[T]he absence of entrepreneurship from our theories of markets, firms, organizations, and change makes our understanding of the business landscape incomplete.”

Disequilibrium and dynamism

The discussion thus far drew attention away from the former neoclassical view of the organization to an “upgraded, more unified, and better-attuned view on strategy’s core issues” (Farjoun, 2002, p. 561). A similar shift took place in economic thought from a neoclassical, allocative view of market processes to the integration of entrepreneurial discovery, creation and innovation. The idea was that the driving force of market processes is not provided by consumers or owners of the means of production (land, capital etc.), but by the profit-seeking entrepreneurs themselves (von Mises, 1966).

A main reason for this shift was due to the obvious inadequacy of the assumption that market conditions are always in equilibrium i.e. the inadequacy of an approach to theory and empirical analysis that assumed it always prevailed, rather than emerged via equilibrative processes (von Mises, 1966; Hayek, 1967a). In fact, one stream of research, also that of Austrian economists, has questioned the meaningfulness of emergent equilibrium in the first place i.e. of an equilibrating force dominating a disequilibrating force (Lachmann, 1976). In other words, although the market process is subject to continuous changes, to so-called ceaseless motion, this stream questions whether there is any tendency toward equilibrium.

The answer is open to debate. Although discovery theorists like Hayek claim that there are dominant equilibrating forces, others object to the notion that the market process is a learning one. In the Rothbard-Salerno view markets are characterized as continual processes of entrepreneurial decision-making rather than of knowledge acquisition (Koppl and Minniti, 2003): entrepreneurs judge things best in an incessantly changing world based on their estimations of expected profits and losses. Market coordination is not considered to be the result of systematic knowledge acquisition due to entrepreneurial alertness, or an ‘entrepreneurial mindset’, but to the ability of entrepreneurs to deploy resources at each moment to their most urgently demanded, consumer-driven, uses (Koppl and Minniti, 2003).

The process is associated with error, Austrian theorists believing that the market is driven by entrepreneurs[7] often surprised by outcomes, rather than by decision-makers who know what they are ignorant about (neoclassical view). It is error and surprise which suggests that if there is any tendency toward equilibrium, it only exists at a particular point in time, creating an incentive for entrepreneurial corrective decisions to be made, rather than being there at all times in progress[8].

Whether or not markets are perceived as dominated by disequilibrative forces or not, they can be perceived as Schumpeterian environments, at any point in time as a process of exchange, in perpetual disequilibrium (Koppl and Minniti, 2003). Following the Austrian school, decision-makers experience these dynamics as a superabundance of diverse, surprising and often apparently attractive opportunities. In highly dynamic markets these opportunities are diverse, rapid, ambiguous and unpredictable (Hayek, 1949).

Risk and uncertainty

As Gifford (2003) states, for there to be any role for the entrepreneur or entrepreneur-manager[9], there must be disequilibrium. This is only the case when there is uncertainty and accompanying risk i.e. imperfect information. But the risk-bearing assumption (Knight, 1957), although empirically supported (Cramer, Hartog, Jonker and van Praag, 2002), does not explain *why* entrepreneurs should be less risk averse than others. Nor does ‘animal spirits’ or ‘irrationality’ explain this, both of which were identified by Keynes and Schumpeter as qualities of the entrepreneur.

Instead of hypothesising that entrepreneurs are willing to take risks, Gifford (2003) considers an alternative, that of the role of human capital investment. By adopting an approach that derives risk-averse behaviour as the result of limited attention, it is possible to observe that entrepreneurs are risk-neutral. The assumption is that the entrepreneur’s goal is to maximise the discounted expected value of all current and new ventures over time (Gifford, 2003, p. 45): “In addition to allocating attention each period, the entrepreneur also

[7] Wickham (1998) distinguishes between different types of entrepreneur (sequential, serial and so on), suggesting their classification may also change over time.

[8] This is the reason why Austrian theorists support laissez faire government policy, since a tendency toward error, unlike Schumpeterian ‘disruptive innovation’, is not assumed. Government regulation is expected to frustrate the coordinative tendency toward error-correction.

[9] Chakravarthy and Lorange (2008, p. 14) use the term ‘entrepreneur-managers’ to describe individuals dedicated not only to creating new ventures, but also to integrating them with the firm, “outward-focused, cognizant of changes on their business environment and the new opportunities these may bring.” For the purposes of this research the terms entrepreneur, entrepreneur-managers and managers are used interchangeably.

chooses which venture to shut down. This action requires no attention... The entrepreneur receives a return from each of the retained current ventures.”

Besides risk neutrality, this hypothesis also assumes that there are alternatives to choose from in the first place, and builds on the explicit notion that different skills sets are required – entrepreneurial ones for the pursuit of new opportunities and managerial ones for current ventures. In all, limited attention theory fits well with early studies of managerial uncertainty that first indicated its importance to complex organizations (March and Simon, 1958; Thompson, 1967) and then also with later studies that noted the effect on performance of the fit between the organization’s information processing demand (as determined by uncertainty) and its capacity (Tushman and Nadler, 1978). It also fits with perceptual views of environmental uncertainty which are process-oriented and seek to describe the stages involved in noticing, interpreting, or learning the environment and that seek to link it with strategy, structure, and performance (Duncan, 1972; Bourgeois, 1985).

Alertness, action and learning

The contributions of the Austrian economists to market and entrepreneurial processes go beyond disequilibrium. Kirzner (1997) defines entrepreneurship as alertness (receptiveness, and ability to use information to create new means-ends frameworks) and seizing of opportunity. On the subject of alertness, Koppl and Minniti (2003, p. 88) write: “Because we cannot step in the same river twice, all our actions contain an element of improvisation. Such improvisation would be impossible without alertness to new opportunities.”

Then, on the subject of seizing and action, they apply a negative test (p. 89, original emphasis): “Imagine someone noticing a price discrepancy, but not acting on it. Why was there no action? If he did not do it, he did not want to, whether for lack of know-how, lack of will, or other causes. If he did not want to, it was no opportunity. It was no opportunity *for him*.” The action part of the process takes place not only in disequilibrium but also in a fleeting timeframe (von Mises, 1966). Order is argued to emerge from this, not because anyone, or any regulatory institution, understands or can orchestrate it, but in a spontaneous manner. It is the result of human action rather than design (von Mises, 1966; Hayek, 1967a).

O’Driscoll and Rizzo (1985) captured this process in terms of the ‘economics of time and ignorance’[10]. They considered learning to be indeterminate but not random i.e. if it took place, then it would be path dependent, each interpretive framework affecting the next. More recent contributions toward a theory of entrepreneurial learning have expanded the character

[10] Here time was subjective (‘real time’), taking surprise and experience into account, in contrast to clock time.

of this part of the process: it is ceaseless and without any guarantees (Harper, 1996), is accompanied by error and neglect (Choi, 1993a) and depends on a preparedness to learn (Koppl and Minniti, 2003). According to March (1994), an explorative approach is required in changing organizational processes, an ability to perceive shifts, and a willingness to live with possible failures and uncertain returns. Despite these contributions, much has still to be done for a complete understanding of *how* entrepreneurs learn (Krueger, 2003, p. 110).

Entrepreneurial cognition

Building on the above issues, particularly disequilibrium and uncertainty, it is useful to consider what cognitive phenomenon is associated with the alertness → action process. According to Acs and Audretsch (2003) this particular field of inquiry offers rich theory and well-developed methods.

To begin with, entrepreneurs appear, according to Krueger (2003, p. 107), “to identify opportunities based on cues or signals from the environment”. However, there is no simple answer as to how they recognize patterns, or how they learn to see opportunities and decide to pursue them. To simplify this complicated process, Dutton and Jackson (1987) modelled opportunity perceptions using the cognitive phenomenon of categorization. They successfully contended that individuals and organizations categorize as many strategic issues as possible into opportunities and threats, issues that are positive and controllable and issues that are negative and beyond control.

They add that these categorizations are “not benign concepts used to summarize objective estimates of the probability of loss or gain” (Jackson and Dutton, 1988, p. 384), and urge researchers to continue to consider the cognitive aspects that form critical perceptions. Grinyer and Norburn (1975) concluded from an empirical study of 21 U.K. companies that successful executives (in terms of size, profitability, performance, growth etc.) focussed attention more on issues and problems than successes, as pointed out by the behavioural economists[11], but also found they failed to keep up with changes in their environments. Mezias and Starbuck (2003), whilst confirming the heterogeneity of perceptions and lack of need for agreement among successful decision-makers, found that most problem solving does not depend on accurate current knowledge of situations i.e. that inaccuracy does not

[11] These researchers did qualify their findings from a causal point of view, and point out the need for longitudinal studies amid the difficulties caused by the multitude of factors affecting performance.

prevent effective action. Although decision-makers may make errors that cause harm, they need only pursue general, long-term goals[12].

In short, decision-makers evidently employ filters, constructs and measures that are based on perceptions, rather than reality (Krueger, 2003). So the role of perceptions is key. However, what distinguishes the behaviour of entrepreneurs from others is the role of intention. Consensus on the notion of useful predictors of intent is well summarized by Davidsson (1991). On the strength of this, Krueger draws together the work of previous researchers in an Intentions model:

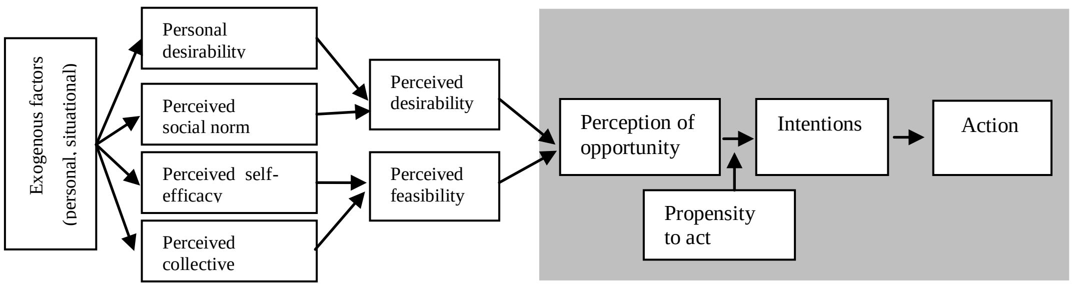

Fig. 2.1. Intentions model

(Source: Krueger in Acs and Audretsch, 2003)

According to Krueger (2003), an advantage of the model is its strong convergence with other cognitive models. As such, it is a powerful and predictive cognitive mechanism. He also notes the implications it has for the organization: if entrepreneurs must perceive more – and better – opportunities, then organizations need to foster, and be seen to foster, those perceptions. What is still missing, however, is a representation of changing intentions and consensus on the direction of causality, Krueger (2003, p. 119): "intentions could be seen as simply another attitude, just more visible".

Furthermore, the observations of researchers regarding time and delays in the intentions – action process is not captured in the model. A key observation is that although organizations change, actions that bring about change are subject to forces that make it difficult for entrepreneurs to control: "What most reports on implementation indicate . . . is not that organizations are rigid and inflexible, but that they are impressively imaginative.

[12] Mezias and Starbuck (2003) have considered the accuracy of managers' perceptions and concluded that the difficulties involved may be compounded by inaccuracies in the perceptions of the researcher themselves.

Organizations are continually changing, routinely, easily, and responsively, but change within organizations cannot be arbitrarily controlled." (March 1981, p. 563).

Entrepreneurial opportunity

Researchers have attempted to define entrepreneurial opportunities in a number of ways. Sarasvathy et al (2003) draw on the concepts of newness, beliefs and actions (thereby synthesising the contributions considered thus far) by suggesting that opportunities consist of:

a) new ideas or inventions that may or may not lead to gains,

b) beliefs about things favourable to the achievement of possible valuable ends, and

c) actions that generate and implement those ends.

Others (e.g. Kirzner, 1997; Shane and Eckhardt in Acs and Audretsch, 2003, p. 165) consider opportunities to be "situations in which new goods, services, raw materials, markets and organizing methods can be introduced through the formation of *new* means, ends, or means-ends relationships... that *have the potential* to alter the terms of economic exchange." Here too, importance is attached to newness, to means and ends 'previously undetected' (as opposed to established frameworks) and to the active introduction of goods, services etc. Again, the ontological standpoint is that action is required for an opportunity to have any meaning.

Sarasvathy et al (2003) use their definition to develop a typology of entrepreneurial opportunities based on three pre-conditions for their existence: 1) neither supply or demand exist, 2) either supply or demand exists, 3) both exist. They argue that opportunities must therefore be created, discovered or recognised, depending on the conditions. Each is empirically valid at some stage of market creation and the call is therefore for their integration, rather than separation.

The first (also arguably the earliest stage), the creation view, has been enriched by a number of models. One, the garbage-can model suggests a process in which choices arise from temporal proximity rather than any means-end linkage (March, 1994). Another, enactment and sense-making theory, suggests people invent things based on their perceptions, thereby blurring any distinction between them and the environment (Weick, 1969). A third, effectuation (Sarasvathy, 2001), brings these non-teleological theories together by casting opportunities as the result of interaction and negotiation about vague perceptions and aspirations, rather than as pre-existent. This view can be matched to that of unknowable futures (Knight, 1957).

The second, the discovery process view, which depends on the existence of either supply or demand, applies to markets that pre-exist or are latent. Here futures are not known. Uncertainty precludes deliberate search, but new information gives rise to potential for enactment. The process is therefore characterized by experimentation (rather than effectuation), surprise and error. The third, the allocative view (opportunity recognition) is regarded as a purely random process with any actor likely to detect an opportunity in a future that is known, but requires some calculation.

Shane and Eckhardt (2003) note that opportunity exploitation cannot take place if opportunities do not exist in the first place. Therefore, according to their model, the process must be a sequential, directional one:

Fig. 2.2. Direction of the entrepreneurial process
(Source: Shane and Eckhardt in Acs and Audretsch, 2003)

The model should not be construed as linear or without feedback loops, nor does it assume the same person engages in all parts of the process, or that perceptions about opportunities will remain constant throughout. The idea is, however, that they are subject to shocks and transience. This fits with earlier research suggesting that opportunities that are able to generate payoffs provide initial incentives for others, who may validate them and thereby fuel demand, but that they are doomed by information diffusion and competition (Schumpeter, 1942; Hannan and Freeman, 1984; Kirzner, 1997).

This section offers an aerial view of some of the relevant issues that shape the business landscape, from an entrepreneurial perspective. It complements those of the previous sections through inquiry into the newness and dynamism associated with the exploitation of entrepreneurial opportunity. In particular, it highlights system attributes such as disequilibrium at a point in time and important cognitive aspects of agents, including problem categorization and uncertainty as a problem of allocating limited attention to alternatives. It also offers alternative views of opportunity capture and two simple, but useful models, Krueger's 'Intentions Model' and Shane and Eckhardt's 'Direction of the Entrepreneurial Process', to capture the key roles of perceptions and intentions in the opportunity exploitation process.

To complete the integration of the above contributions with the principles of complexity and ABMS, the next section discusses some of the key elements identified by complexity theorists as being characteristic of CAS, the difficulties researchers face in modelling CAS, and recent developments toward advancing this field of inquiry. Again it places this research in an historical context, and considers its roots and evolution up to currently prevalent thought.

2.1.3 Modelling CAS

In tracing through the contributions of researchers to our understanding of CAS and the implications of modelling these, this section also covers contributions that have roots in other fields of inquiry. It exposes the sometimes arcane terms and concepts that are applied, and identifies characteristics commonly associated with CAS. In all, it points to the increasing importance and implications of viewing organizations as CAS, and the progress of researchers towards more effective experimental science.

CAS

There have already been a number of references in this chapter to concepts that have roots in complex systems thinking, and to researchers who have contributed to this field of inquiry. Section 1.1. referred to the shift in perspective from decision-makers as rational, utility maximisers to sub-rational satisficers, to Simon’s representation of strategic means-ends frameworks as hierarchical in nature, and to the Nelson and Winter and North and Macal models, that build on the notion that ‘history matters’. Section 1.2 referred to March’s suggestion that an explorative approach to exploitation and learning would apply in changing organizational processes, and to Weick’s enactment and sense-making theory which tends to blur distinctions between actors and environment. The ensuing review helps to explain the origin, significance and implications of these contributions.

System complexity has been understood variously to include ‘a large number of interdependent parts within a larger environment’ (Thompson, 1967), or ‘a large number of interactive components’ (Simon 1996). For organizations complexity refers to ‘a large number of activities or subsystems in an organization’ (Daft, 1995), and for strategists to ‘a large number of configurations considered in shaping strategy’ (Chakravarthy, 1997). Organizations can be considered complex in a number of different ways, structurally, technologically, environmentally and so on, wherever the number of interdependent elements is large.

Although the study of complex systems is still regarded as a relatively new approach to science, its roots are traceable to researchers' interest in holism almost 100 years ago. Cyberneticists' interest in complex systems grew in the 1950s, followed by general systems theorists who began developing underlying principles for all systems with components linked by feedback loops (Anderson, 1999).

A number of theories followed (e.g. general systems, catastrophe and chaos theories) construing systems as following dynamic paths determinable by a set of equations. Simon (1996) characterizes these systems through a 'stretching and folding' operation – stretching of the variables magnifying the system and sending it into different regions of the state-space, which are folded or constrained into limited regions of attraction.

Their behaviour, though not random, may be chaotic, making it unpredictable and surprising. Small shocks, small changes in only one or two parameters, can greatly affect the whole system in nonlinear fashion, referred to as the 'butterfly effect'. This is what makes these systems complex. The whole of the system is no longer the sum of the parts, and it escapes parsimonious description (Simon, 1962; Casti 1994). The result is very often the emergence of unexpected structures and events that have properties very different from the component parts, unpredictable, with sudden transitions and irregular patterns.

Such systems, including organizations, are regarded as complex and as having adaptive capabilities. Using these principles, organizational complexity theorists have built systems more open to the environment and with loose component coupling, more applicable to organizations (Weick, 1969; Katz and Kahn, 1978). Still lacking a unified set of principles though, Anderson (1999) has identified four elements with 'interesting implications' for organizations: 1) agents with schemata, 2) self-organizing networks sustained by importing energy, 3) co-evolution to the edge of chaos, and 4) system evolution based on recombination.

The first assumption is that outcomes are produced by dynamic systems comprised of agents (individuals or groups) at a lower level of aggregation (Holland, 1995). Their behaviour is dictated by a schema, a cognitive structure that determines agents' actions depending on their perceptions. *Agent schemata* may be flexibly operationalized, modelled as fixed or fuzzy rules that may or may not differ among agents and may or may not change over time.

Second, agents are connected to one another by feedback loops (like variables in systems dynamics models), and act on local information derived from them. The information and agent actions (decision-making, hiring, firing and so on) maintain the system, preventing it from ‘dissipating’[13], without the need for any central organizing control (Prigogine and Stengers, 1984). The idea is that no external interference, no special or initial conditions, nor any global purposefulness on the part of the individual agents, are required for the system to *self-organize* i.e. attain a desired order. In other words, it is not necessary to assume that agents are able to forecast outcomes at any level of the system, they may well suffer from limits to attention, but successful outcomes are possible as a result of pursuing their own local goals (March and Simon 1958; Holland, 1995).

Third, in their ‘efforts’ to achieve their rule-driven goals, agents *co-evolve,* that is, the choices they make are interdependent, one’s choices depending on the others. Agent behaviour (as determined by the choices made) therefore shifts continuously (Levinthal, 1997). Small changes either self-correct, with the system remaining in an attractor state, or the system evolves toward a critical state at or near the *edge of chaos,* with small shifts affecting outcomes in a variety of ways, according to a power law (Bak, 1997; Morel and Ramanujam, 1999). According to these researchers, this can result from selection, the weakest agent being replaced by a random substitute (in organizations, this would be part of the hiring and firing process) or through recombining existing agents or schemata. This then sets off further cascades of co-evolutionary adaptation.

The fourth assumption is that complex, adaptive systems (CAS) evolve over time through *recombination*. Links between agents shift and evolve, agents enter and exit the system and are themselves transformed. Andriani and McKelvey (2006, p. 7) sum up: “As time progresses, each agent makes connections and then may co-evolve with other agents, perhaps a little with all of them at first but then positive feedback sets in with some negative feedback with others and some mutual causal relationships expand and others contract. The result may be the formation of networks and perhaps groups of agents, that is, new order. Assuming that the set of agents is large enough and enough time passes, a power law arrangement of connected agents and perhaps newly formed groups (agents) results.”

For fear of drifting too far from its academic roots in applying the lessons of complexity science, researchers have attempted to refocus thought on its foundations, specifically on the changes in the nature of the dynamics involved (Stengers, 2004; McKelvey, 2004). These authors remind organizational researchers that complexity science originated with difficulties explaining the emergence of dissipative structures in CAS (implicit therein, the questions of determinism and equilibrium), and is hence concerned with the creation of order. Explaining systems that are not deterministic, predictable and reversible, but that have

[13] The term is applied to open, far from equilibrium, systems that exchange energy, matter, information etc. with their environments, originating from the study of thermodynamics.

stochastic elements (random, probabilistic or deterministically chaotic), has proved intractable for 'normal', positivist approaches to science. The implications are twofold: complexity-science is, more aptly, order-creation science and the positivist approach to modelling CAS needs revision.

In sum, there is no agreement on a definition of complexity or the basic principles of a complexity theory for organizations in the literature. As long as complexity emerges, different schools of thought and terminological preferences will prevail. Definitions relating to complexity range from the simple and precise to the general and inclusive. The simplest definition is that complexity is variety, that is, the number of system variables and parameters. The most general and inclusive is that order creation science includes chaos theory, nonlinear dynamics, complex systems theory and self-organization theory (Morcöl, 2001). Morel and Ramanujam (1999, p. 278): "Complex systems theory is not so much a single theory as a perspective for conceptualizing and modelling dynamic systems."

Certain characteristics that fit with this perspective, that are associated with order-creation science, are reasonably clear (Cilliers, 1998; Anderson, 1999): CAS are open systems consisting of many parts, each unaware of the behaviour of the system as a whole; interaction takes place within and beyond the system in dynamic, nonlinear fashion, with positive and negative, direct and indirect feedback loops; memory and intelligence reside throughout the system, facilitating path-dependent, adaptive self-organizing behaviour that is emergent and nondeterministic i.e. is not predictable from an inspection of the parts.

Modelling CAS

Studies in strategic management have roots in the epistemology of economics, which drew on classical physics and hence the concepts of equilibrium dynamics best modelled by mathematics (Besanko, Dranove and Shanley, 1996; McKelvey, 2004). Many researchers regard mathematics as having been especially useful for modelling phenomena and behaviours to gain a better understanding of their empirical or theoretical roots for 'mirroring' theory or phenomena, but only without changing the 'chemistry of the ingredients' (Morgan and Morrison, 1999; Boumans, 2000).

However, being able to 'change the ingredients' (metaphors, analogies, empirical data, stylized facts etc.) evidently improves the model outputs. McKelvey (2004) cites three heroic assumptions[14] at the root of this 'math molding': homogeneity, agent or data point

[14] Heroic assumptions "allow systems to be simplified enough to be modeled using traditional tools… [They] reduce the level of detail in systems and reduce the ranges of allowed interactions between components." (North and Macal, 2007, p. 4).

independence and equilibrium[15]. Taken together, by focusing attention on global dynamics, stability and determinism, they neglect the individual dynamics and uncertainty considered to be indispensable to modelling and theorizing human behaviour.

Byrne (1998) adds that the development of methods of regression to establish the laws of nature only works “if nature is simple and unconscious” (p. 65). Longitudinal statistical modelling, provided all aspects of the system are known exactly (initial position, forces etc.) can exhibit fit, both forwards and backwards. But, as Byrne notes, absent this accuracy, admit butterfly effects, dispense with linearity and the arrow of time – each a key characteristic of CAS – and predictability is felled. Hence “attempts through the development of regression methods to establish social laws... have all collapsed.” (Byrne, 1998, p. 60). Maths models, suitable for the rigorous and accurate translation of energy and matter under ‘normal’ science conditions, appear unable to help explain the emergence of dissipative structures typical of CAS. If math models cannot handle order creation, McKelvey asks (2004, p. 6): “How to get from equilibrium-based to order-creation science?”

Modelling and simulation

Although definitions of modelling and simulation vary, modelling primarily addresses relationships between models and ‘real’ systems, whereas simulation primarily addresses relationships between computers and models (Zeigler, 1976). Human minds are simulators, though not very capable ones, even with the aid of notebooks (Miller, 1956) and spreadsheets (North and Macal, 2007). However, computers have changed things. Their power lies in the ability to explore many plausible paths, structures and predictions, whether run on abstract specifications or collated data (Carley, 1996; Frank and Troitzsch, 2005).

In practical terms, simulation, or computational modelling, permits experimentation through manipulation of the critical variables and constructs over a range of values by changing the software code (Zott, 2003; Davis et al, 2007). For Davis et al, it is useful in particular “for theory development when the focal phenomena involve multiple and interacting processes, time delays, or other nonlinear effects such as feedback loops and thresholds.” (Davis et al, 2007, p. 483). For its explorative and elaborative virtues, these authors place simulation in the ‘sweet spot’ between theory-creating (e.g. using inductive

[15] McKelvey (2004) identifies four forces that evidence the falsity of the equilibrium assumption: 1) rapid changes in the competitive context of the firms, 2) instability, diversity and nonlinearity 3) changing basins of attraction, and 4) agent co-evolution to higher level structures.

multiple case studies and formal modelling) and theory-testing research (e.g. using multivariate, statistical analysis).

In general, researchers aim first to identify principles they believe apply to the target or 'real' world, formalize them by constructing models, then use these within the simulation process to explore, test, learn and understand (Morgan, 1984; Law and Kelton 1991). Much of the value lies in precision and transparency, and hence simulation's ability not only to restate existing theory but also to extend new theory (Davis et al, 2007). Often, when interim states and emergent behaviours are of particular interest, 'behaviour-over-time' graphs can expose these and the underlying complexity of the system, revealing behaviours that are often counter-intuitive (Axelrod, 1997; Sastry, 1997; Resnick, 1998 etc.).

Axelrod and Tesfatsion (2008) assert that simulation differs from standard ways of doing science because of its differing goals and methods of implementation. They list the goals of ABMS researchers as empirical, normative, heuristic, and methodological in nature. *Empirical goals* refer to the search for aggregated patterns and outcomes where central authority is absent and for causal explanations e.g. Vicsek et al's Mexican Wave. *Goals of normative understanding* refer to the use of ABMS as laboratories for discovering better design and performance and establishing efficiency or fairness e.g. models of voting and auctions. *Heuristic goals* refer to the search for not-so-obvious causal mechanisms in social systems e.g. Schelling's urban residential segregation model. *Goals for methodological advancement* refer to the development of tools for improving methods of experimentation e.g. methodological principles, programming practices, evaluation tools etc.

So for these, and many other CAS researchers, for situations where data is difficult to access, simulation, by generating data for observation, is a third way of conducting scientific research (Axelrod and Tesfatsion, 2008). Davis et al (2007) also point out the effectiveness of simulation for developing 'simple' theory, as opposed to developing established theory or theory creation [16]. According to these researchers, the features of simple theory that are particularly well served by simulation, by 'exploration and elaboration through computational experimentation', include undeveloped theoretical precision and a lack of internal validity.

So the argument is that simulation actually thrives off lack of precision and incomplete theory in order to be able to provide any insights. Conversely, in the case of well-developed theory, such payoffs are considered fewer and further between, and where theory is non-

[16] These authors refer to simple theory (see Chapter 1) as undeveloped theory, consisting of limited/modest constructs, propositions, or empirical/analytic grounding, with *some* theoretical understanding of basic processes, but *vague* understanding of interactions.

existent, payoffs are beyond reach. The idea is that there should be both sufficient theoretical development and room for improvement, for simulation to be of maximum value.

Support for modelling and simulation

The potential for generating data for theory development through simulation has resulted in growing support for simulation research. Authors single out simulation's ability to generate both complex behaviour from simple models and simple behaviour from complex assumptions (e.g. Parunak et al, 1998; Gilbert and Troitzsch, 1999; McKelvey, 2004). They note simulation's ability to facilitate better exploration of the dynamics of CAS, and its potential in overcoming the traditional techniques of science through more holistic approaches – for example of overcoming the "uneasy feeling that there is something quite eerily inhuman about... the utility maximising individual" (Marney and Tarbert, 2000, 5.13).

Another claim for simulation research is its strength in overcoming the weaknesses of alternative methods in particular research contexts. For example, phenomena typical of CAS, involving many interactions and nonlinear effects are better explored using an experimental approach that can cater for complexity with the aid of computers, than they are using traditional statistical techniques, or purely intuitive methods. This is not to say that computers are a substitute for thought (Lindley, 2006), but that they permit a wider range of experimentation.

Much of the effectiveness of simulation, according to Davis et al (2007), depends on the research question itself. These authors regard relationships between variables that produce fundamental tensions[17], and that result in nonlinear behaviours typical of CAS, such as tipping points and phase transitions, as predestined for such an experimental approach: boundary conditions and steep thresholds are more easily sought and tested-for using simulation than purely inductive case methods and other more traditional techniques. After the model is in operation, both the constructs and program can be adjusted as often as necessary and reasonably quickly, enabling the simulation scientist to cycle back and forth between inductive and deductive methods. This is normally a far more challenging task for empirical researchers once they have collected their data.

Epstein (2008) offers a long list of reasons to build models. Importantly, they can explain (not the same as predict); guide data collection; illuminate core dynamics; suggest dynamical analogies; discover new questions; promote a scientific habit of mind; bound (bracket) outcomes to plausible ranges; illuminate core uncertainties; offer near-real time

[17] Davis et al's 2007 model, for example, addresses the tension between too much versus too little structure in organizations.

crisis options; demonstrate tradeoffs, suggest efficiencies; challenge the robustness of prevailing theory through perturbations; expose prevailing wisdom as incompatible with available data; educate the general public, and reveal the apparently simple (complex) to be complex (simple).

In spite of all these possibilities, simulation is not without its critics. Binmore (1998), for example, questioned Axelrod's (1997) claims in favour of the tit-for-tat strategy and bemoaned "his unwillingness to see what theory can do before resorting to complicated computer simulations". This particular disapproval has been addressed[18], with Marney and Tarbert (2000) in fact pointing to a more general treatment of such reservations by grouping them under the mantles of unorthodoxy and manipulation. The best response to avoid being perceived as directly challenging orthodoxy, they argue, is through careful justification or cross-mapping[19]. The best response to accusations of manipulation is the reminder that all models are to some degree artefact, and one of the main points of science is to explore and test abstractions and metaphors for what they teach about the world.

Another reservation some researchers have of simulation relates to research ethics. Some modellers may be unable or insufficiently motivated, to provide a complete and accurate description of all the important assumptions of the model, or to exercise an appropriate degree of caution when interpreting the results or making claims for contribution (North and Macal, 2007). In abstracting away from the target, the very reason for performing simulation, how far removed from the target can the modeller progress, before the representation loses its utility?[20] This is a matter of degree, but points to a need for awareness and caution when interpreting the simulation outcomes.

In sum, despite the difficulties some researchers have with experimentation in organizational science, the importance of models to 'effective science' and the strength of the link between this and computational modelling already appears beyond question (Casti, 1997; McKelvey, 2004). Researchers have, along the way, repeated the contention that there is probably no other way of modelling complex systems than through simulation (Epstein and Axtell, 1996; Gilbert and Troitzsch, 1999; Marney and Tarbert, 2000).

[18] By attaching less importance to the global rationality of the agents, Axelrod's model fails the test of orthodox neoclassical economics, but not of behavioural economists.

[19] Ziman's cross-mapping principle, by allowing for the re-emergence of orthodox theory, is argued to benefit all science, but especially social science where ontological adequacy (see next Chapter) is often shaky by orthodox, positivist standards.

[20] In a parallel to the Milgram experiments (1963), the behaviour of people playing simulation games changes when they are far enough removed from reality.

Approaches to modelling and simulation

Scientists experimenting with modelling and simulation adopt a number of different approaches. Davis et al (2007) distinguish between structured, more constrained approaches and stochastic, customized approaches. Structured approaches, if not modifiable in relevant ways, can impose unwanted constraints on the researcher, for example:

1) Systems dynamics, a top-down aggregated approach with a broad range of application, is equation-based and tends to be too deterministic for stochastic systems[21];
2) NK models are able to test a system's ability to search for and optimize its fitness based on the number of nodes (N) and interactions (K) that take place within it, but is restricted in its ability to capture market dynamism and node heterogeneity (Davis et al, 2007);
3) Genetic algorithms overcome the heterogeneity problem associated with other optimization approaches, capturing system adaptation through variation-selection-retention processes consistent with human learning (Anderson, 1999), but again are not as useful when performance metrics change, as is the case with dynamic markets[22] (Davis et al, 2007);
4) Cellular automata, in spite of their all-round flexibility and ability to produce macro-level emergent patterns, tend to impose unwanted geographic constraints on models due to their geometric nature (Lomi and Larsen, 1996; Anderson, 1999).
5) Computational mathematics systems (e.g. MATLAB, Mathematica) support rich mathematical functions and generally have sophisticated outputs, but are more difficult to learn, and remain limited in their scalability.

The message, in short, is that both structured and stochastic approaches, depending on the particular circumstances of the research, are able to serve the modeller's purposes. Table 3.1 below shows some of the different approaches adopted by researchers.

[21] North and Macal (2007, p. 55) point out that systems dynamics is more a 'way of viewing the world' than a simulation technique.
[22] Morel and Ramanujam (1999) regard genetic algorithms as appropriate only when there is a known function to maximize, which cannot be said of co-evolving organizations when definitions of what it is trying to optimize shift.

Study	*Research Question*	*Key Processes*	*Approach*	*Representative Findings*
Sastry (1997)	How do organizations undergo fundamental change?	Change and inertia	System dynamics	An additional negative feedback loop corrects theoretical logic of punctuated equilibrium theory.
Lomi & Larsen (1996)	How do competition and legitimation affect density dependence?	Competition and legitimation	Cellular automata	Neighbourhood size moderates the relationship of density with founding and failure rates.
Rivkin (2000)	What is the optimal strategic complexity?	Replication and imitation	NK fitness landscape	Moderate strategic complexity is optimal.
Davis et al (2007)	What is the optimal degree of structure?	Improvisation	Stochastic processes	Unpredictability (not ambiguity, complexity, or velocity) is the driver of the tension between structure and chaos.
Mitteldorf and Wilson (2000)	How can nature select a gene that promotes the fitness of others at the expense of the bearer?	Cooperation and altruism	Agent-based	Population viscosity can support both weak and strong altruism when population density is allowed to fluctuate.

Table 2.1. Recent examples of simulation research
(Adapted from: Davis et al, 2007)

North and Macal (2007) also note that deterministic models, vis-à-vis stochastic models, are simpler and less expressive, always producing the same outputs from certain inputs. These researchers point out that such models tend to disregard the inevitability of approximation caused generally by inherent bounds on certainty, and specifically by bounds associated with business, due to lack of information, imperfect data collection and so on. Typically, mirror-world models are 'validated' by comparing outputs to data, but powerful as they are they cannot be applied to open systems where prediction is not possible due to complexity and uncertainty (Bankes, Lempert and Popper, 2002).

Stochastic models on the other hand include random or probabilistic model elements. They can produce different outputs from the same inputs, usually requiring many simulation runs for a pattern to emerge or to produce a useful result. A single run merely produces one narrative, a single possible behavioral path. "The assumption is that agent behaviors or environmental responses are not known with complete certainty, so these factors are characterized by ranges of possible values, means, variances, and other statistical measures." (North and Macal, 2007, p. 12). In such cases, when surprise is ultimately assured, a framework consisting of computational experimentation using an exploratory platform is considered useful. From this perspective, experiments are performed that produce outcomes supportive of the articulation of credible arguments (Bankes et al, 2002).

Computer scientists treat this variation as ‘stochastic uncertainty’, irreducible variability resulting from system behavior that prevents precise outcomes. Despite this, modelling makes sense: even if variation cannot be predicted, it can be useful to identify ranges, boundaries, paths and patterns (Berleant et al, 2003; North and Macal, 2007).

Furthermore, variability may also be due to lack of facts or information, filled in by guesses and approximations during the modelling process, a useful research exercise in itself. In other words, these researchers recognize that even if the only perfect model of a CAS is the CAS itself, it may not be necessary to include all the details. So even if much of the model is simply an approximation, the discovery of interesting and useful patterns and behaviours may open up avenues for learning.

Further considerations relate to model use, efficiency and human resources. Here North and Macal (2007) point to the need to distinguish between modelling structures i.e. between one-stop modelling, generalist and specialist modelling. When the task of model author and implementer are split, it might improve efficiency, but equally it could hinder replication efforts. Wilensky and Rand (2007) therefore recommend that model authors implement their own models.

North and Macal (2007) note that one-stop modelling requires a single highly-motivated individual with a full range of modelling skills to do all of the work, thereby placing limits on effort and skills inputs. They therefore recommend that modeller’s develop a foundation for further modelling efforts, suggesting balancing current and future research requirements. For one-stop modellers the focus, in their view, is on developing a) a clear grasp of the problem and awareness of the area being modelled, b) an understanding of agent modelling, c) knowledge of a model development tool, d) data collection skills, and e) capabilities with model output analysis and presentation.

So, although the perfect model of a CAS may only be the CAS itself, simpler descriptions containing only those of interest, applying Occam’s Razor[23], can suffice. Although this opens the door to one-stop modelling, the challenges of how much detail to shear away and how to simplify and make generalizations about simulation outcomes remain (Anderson, 1999; Morcöl, 2001; Ormerod, 2008). As Anderson (1999) points out, it is not necessary for scholars applying ABMS to understand all of the parts of a complex system holistically. Instead, they can focus their attention on agents locally, employ ‘artful approximation’

[23] Occam's razor is a logical principle attributed to the mediaeval philosopher William of Occam (or Ockham), which states that one should not make more assumptions than the minimum needed. http://pespmc1.vub.ac.be/OCCAMRAZ.html.

(North and Macal, 2007), vary the assumptions about their schemata, interactions and so on – test these out with fixed or fuzzy rules – and hence cycle back and forth between inductive and deductive methods.

Here Edmonds and Moss (2005) differentiate between two approaches, depending on the problem and the expectations of the modeller. The first, 'Keep it descriptive, stupid' (KIDS) envisages the capture of target phenomena by drawing on the widest possible range of evidence, including sources such as anecdotal evidence and expert opinion. The model is then only simplified if justifiable. This approach contrasts with the second, 'Keep it simple, stupid' (KISS), which starts off with a simple, baseline model and only extends it if forced to.

The usefulness of the new KIDS approach is obvious when the target is dominated by complex phenomena and there is no reason to expect a very simple, elegant model to be particularly useful (Edmonds and Moss, 2005). However, the appropriate approach depends on the problem context, and represents a trade-off between what is descriptively adequate versus what is practical. This can result in complex mixtures of both approaches. Either way (at least when pursuing empirical, normative or heuristic goals), the intention is usually to first use the model and simulation as a platform from which to contribute to the development of theory, and then to pursue the simulation process through further verification and experimentation at the next level (Stinchcombe, 1968).

2.1.4 ABMS

Much of the above discussion on simulation applies to ABMS. In a follow up to their 2007 book, North and Macal (2008) distinguish between ABM (agent-based modelling) and ABS (agent-based systems or simulation): in ABM, agents repeatedly interact with the purpose of achieving a desired end-state, whereas in ABS agent interaction is simulated over time in order to capture the dynamic processes of agent interaction per se.

The broad aim of ABMS is to place agents – 'intelligent', autonomous programs of various levels of sophistication – in a computational framework in which they interact, among themselves and with their environment, without any central authority, and to leave the computer to build up the complexity of the whole, from the bottom up (Gilbert and Troitzsch, 1999; North and Macal, 2007).

ABMS is founded on the notion that "the whole of many systems or organizations is greater than the simple sum of its constituent parts" (North and Macal, 2007, p. 10). For ABMS, systems or organizations fit with those of the previous section i.e. are observably

CAS. They are understood as ‘collections of interacting components’, each contributing to the system in some way, yet each following its own set of rules and responsibilities. Components are heterogeneous, meaning that some may have more influence on the system than others, but that none is in complete control of the system’s behavior (Gilbert and Troitzsch, 1999).

ABMS’ roots are in Distributed Artificial Intelligence[24], which addresses systems with many interacting components that possess some level of autonomy, that is, components that are able to perceive their environment and react to changes in it, depending on their goals. ABMS makes strong use of this component, or bottom-up, paradigm as an approach to system design. Lower-level behavioural rules are specified first, then higher-level or aggregate specifications (North and Macal, 2007). A bottom-up approach does not rely on any centralized system control, instead system level outcomes are expected to ‘emerge’ autonomously from the component rules and interactions. Emergence is a feature of ABMS, placing both the approach and techniques of analysis within the domain of complexity research (Holland, 1998).

ABMS begins at the agent decision-making level – not the black-box of statistical modelling or process level of discrete-event modelling. Agents are placed in a computational framework and the computer is left to ‘grind out’ their interactions (North and Macal, 2007). Despite the fundamental differences in coping with the limitations of traditional approaches, ABMS borrows off them[25] in dealing with agent interaction, time and scheduling. North and Macal refer to this as ‘blended modelling’. They point out, for example, that ABMS can be combined with discrete-event modelling process techniques to model consumer movement through a store; combined with statistical modelling to estimate agent behaviours or the statistical relationships between the variables that govern them; and combined with optimization approaches, when agents’ behaviour is believed to come reasonably close to optimization rather than satisficing[26].

In doing so, ABMS is able to capture much of the complexity, many of the characteristic features of CAS (nonlinearity, unpredictability, amplification of small variations and so on), in a manner previously considered impractical. It provides a platform for viewing the possible individual and system configurations that might evolve from the specified rules. Resnick’s model of the behavior of ants is a simple example revealing the macro-laws that govern its surprising flexibility, emerging without a detailed knowledge of the individual

[24] Now referred to as Multi-Agent Systems, MAS.
[25] North and Macal point out that the converse is not necessarily true.
[26] Examples include genetic algorithms, applied widely to business problems, and swarm optimization, motivated by observations that apparently intelligent behaviour can emerge from simple organisms through behavioural adaptation and improvement.

ant's behavior. Yet, as North and Macal (2007) note, examples also abound of models with human agents following simple, satisficing rules that replicate interesting stylised facts i.e. that do not try to solve multi-period optimisation probability and that produce surprising, emergent behaviours at the system level.

Agents

As the name implies, Agent-Based Modelling and Simulation, ABMS, focuses on agents. The individuality of agents is normally important. They are heterogeneous and autonomous, so they are, in a sense, active rather than passive. This is what makes them distinctive. North and Macal (2007) note that there is no universally agreed definition of an agent. Some modellers consider agent independence sufficient (Bonabeau, 2002), others expect adaptive, learning capabilities, or 'rules to change the rules' (Casti, 1997). However, they embrace a pragmatic view of agents, from the simple or proto agent that may lack some of the above characteristics to the complex agent able to follow multiple, complex and nested rules. North and Macal (2007) note that in the process of ABMS, proto agents may be transformed into complex agents (and complex agents into advanced technique agents) by adding one or more characteristics, as the need arises.

Agent intelligence is the topic of ongoing debate. Some researchers suggest the need for proactive agents (able to pursue goals persistently), reactive agents (able to respond to environmental changes in a timely manner) and social agents (able to interact with one another). Others suggest the need for more specific processes, mechanisms and functions, which themselves seem to create a need for further specifications – a type of Pandora's Box of concerns for distributed artificial intelligence and multi-agent systems.

On the question of whether modellers are particularly concerned about agent intelligence, Tesfatsion[27] writes: "[although] some ABM researchers have indeed concentrated on simple agents in an attempt to understand the manner in which complicated phenomena can arise from repeated interactions AMONG agents rather than from any complexity inherent in the structures of the individual agents per se, [others] have focused on the use of ABMs to study issues arising for real-world systems… there is most definitely a concern that the agents in the ABM appropriately reflect the characteristics of their empirical counterparts, including their intelligence characteristics. Whether this objective is achieved can be debated, of course, but I would certainly say that the concern is there."

[27] SIMSOC e-mail communication, August, 2008.

On Tesfatsion’s point about trying to reflect the characteristics of real-world intelligence in their agents, Olner[28] uses ‘The Game’[29] as an example: “[V]itally, in the real world it doesn’t matter that the humans playing it are capable of more complex behaviour. The point is, they’re ‘enacting’ the rules of a simple game, and those rules exactly mirror what we see in the model. When modelling this - and in the case of reality - we can ignore everything else about those people, whilst they're playing the rules of that game. The same could be said for, e.g., markets. People play games, and the rules of those games can cut through great swathes of meat-world complexity.”

Ormerod (2008) asks: “Were agents so smart, would we not observe much lower rates of [firm] extinction than we do?” In fact, some researchers have modelled zero-intelligence agents (e.g. Fama and French’s model of market volatility), others very simple ones (Epstein and Axtell’s Sugarscape; Vicsek et al’s Mexican Wave). Epstein and Axtell’s Sugarscape model (1996) also highlights the occurrence of evolution and revolution, of punctuated equilibrium, caused not by external shocks, but agent interaction.

North and Macal (2007, p. 8) sum up: “Agent-based modelling works by applying the concept of a wave in a crowd. Each person or agent makes small, simple movements, but the group as a whole produces complex large-scale results. The resulting wave represents the large-scale system outcomes that every leader needs to know about ahead of time.”

Resnick’s ant colony (1998), which emerges from simple rule-following individual ants interacting in a fluid, shifting network, is an example of how a persistent, flexible organization emerges from relatively inflexible components. The stock market, which emerges from restricted buyers and sellers interacting in a complicated dynamic environment, is another. So is the human CNS, which emerges from interconnections and interactions of neurons that are essentially wired into place (Holland, 1998).

North and Macal (2007) note that, as the independent decision-making components in ABMS, agents often represent employees or groups of employees in organizations. At this level, typical agent attributes are their demographics and preferences. At the upper organizational level typical attributes are resources and targets. Typical behaviours are how agents make decisions, communicate, act and respond to change. Their decision-making can be programmed to be rational or sub-rational, their information-gathering and processing ability unlimited or limited, and the rules they follow made to cohere with any range of behaviours considered to be realistic: the challenge is finding and representing them, the task one of ‘artful approximation’ (North and Macal, 2007). This is a flexible way of designing

[28] SIMSOC e-mail communication, August, 2008.
[29] ‘The Game’ demonstrates the power of simulation as a tool for understanding the dynamics of complex systems (http://www.icosystem.com/game.htm).

how the elements of a system behave and interact, one in which the results are computed rather than analytically solved (Richiardi, Leombruni, Saam and Sonnessa, 2006).

Support for ABMS

Agents, whatever their individual endowments (attributes, decision-making capabilities, rationality, learning mechanisms) are what free modelling and simulation from analytical methods and enable ‘bottom-up’ development through algorithms. They give multi-agent systems what Gilbert (2007) calls an additional ‘gear’, compared with traditional modelling and simulation methods. The following three lists show support for the growing usefulness and suitability of this method to organizational research.

First, McKelvey (2004) proposes that ABMS facilitates the accomplishment of several objectives that have a bearing on organizational dynamics:

1) formal modelling without compromising post-positivist ontology e.g. complexity, heterogeneity, indeterminate social behaviors, mutual causality;
2) extraction of more plausible, possibly more parsimonious, theory through experimentation (based on complicated case study narratives that are contextually bound);
3) reduction of ‘complicated theories about a complex world’ through abstraction, leading to explanations of order creation and the formation of norms (hierarchies, structures etc.); and
4) extraction of theories with more empirical truth plausibility that better represent the entire, relevant state-space and are tested against aspects of the observed world.

The implications are pragmatic: more elegant theories offer simpler, ‘more plausibly true’ beliefs, and facilitate clearer research messages to practitioners – of particular importance for management researchers.

Second, North and Macal (2007) reel off a list of situations when ABMS might be applied:

1) the problem has a natural representation as consisting of interacting agents;
2) decisions and behaviours can be defined discretely (within well-defined boundaries)
3) agents adapt and change their behaviour;
4) agents learn and engage in dynamic strategic behaviour;
5) agents have dynamic relationships amongst each other (relationships form and dissolve);
6) agents form organisations;

7) agent adaptation and learning are important at the organisational level;
8) agents have a spatial component to their behaviours and interactions;
9) the past may be a poor predictor of the future;
10) scaling is important, and scaling up consists of adding more agents and agent interactions;
11) process structural change needs to be a result of, rather than input to, the model.

Third, Parunak et al (1998) list the following more specific advantages of ABMS:

1) recognizes a world that includes individuals and observables, each with a temporal aspect, and hence potentially more realistic than other model types;
2) sets boundaries for agents, allowing for different levels of abstraction;
3) articulates agent rules and relationships (strategies), enabling prediction of system behaviour (performance) over time;
4) allows for system and aggregate level definition of observables;
5) supports ease of construction;
6) supports direct experimentation; and
7) supports 'validation' at both the individual and system levels.

Each of these features contributes to the first in the list, the ability to capture the temporal aspect.

In short, it is increasingly difficult to ignore the evidence these researchers have assembled in favour of ABMS, evidence that challenges the fundamental assumption that complex worlds are best understood through top-down approaches. This is supported by the recent proliferation of multi-agent events, workshops (e.g. www.aamas.org, www.scs.org, www.essa.eu.org) and software packages (e.g. Swarm, www.swarm.org; NetLogo, www.northwestern.org; SimSesam, www.simsesam.de).

Performing ABMS

North and Macal (2007) point out that it is possible to perform ABMS on standard office computers using spreadsheets, dedicated simulation toolkits and computational mathematics systems. These researchers consider current spreadsheet programs to be useful for early exploration with agents and capable of deepening modellers' understanding of the research domain, although their low cost is accompanied by limitations in managing size, complexity and diversity.

Simulation toolkits, besides the merits of their visual orientation, are more specialized than spreadsheets and some have special participatory and other large-scale features.

Although they are ultimately also limited in their flexibility and scalability, they generally provide the support mechanisms required for model execution e.g. automatic activity scheduling and data tracking (North and Macal, 2007). Some of these environments (e.g. Swarm, Repast, NetLogo) have free, open source libraries with a range of models, enabling 'borrowing' of model components. The focus of packages like Repast and NetLogo on agent modelling has produced streamlined coding i.e. Python scripting and a version of Logo programming language respectively.

Efforts to develop guidelines for constructing and using simulation models are ongoing (e.g. Edmonds, 2000; North and Macal, 2007; Davis et al, 2007). One recently proposed 'roadmap for theory development using simulation' (Davis et al, 2007) envisions a three-step process: 1) constructing and verifying the computational representation 2) performing experiments with a view to contributing to novel theory, and 3) facilitating model 'validation'.

Constructing models of organizations, as indicated earlier, calls for artful approximation because the behaviours of the individuals (and most components in CAS) are not known with certainty (North and Macal, 2007). As a result, agent and environmental actions and reactions are based partly on random and probabilistic elements i.e. they are characterized by ranges of possible values, means etc. A single run therefore only produces a single possible sequence of events, a single path or system trajectory. The model is run many times (sampling problems only being a concern for field-based studies), producing many paths, none of which can be accurately predicted. Although this uncertainty cannot be reduced, the possible paths and bounds are a source of useful information (Casti, 1994; Epstein and Axtell, 1996; McKelvey, 2004).

Artful approximation is also embedded in the process because of the general need to balance the cost and benefits of added detail (North and Macal, 2007). For these authors, the aim is to capture as much detail on the process of interest as possible whilst approximating the rest. They suggest that the question for modellers, whether or not to include a particular behaviour or property, is the significance of its expected effect: if low, it is excluded and if moderate, it is treated as a marginal candidate. For them, the complicatedness of a particular behaviour, and whether it has been modelled before, is an additional consideration.

Although agents and components routinely follow sets of rules, goals and intentions often relate only loosely to actual behaviours (March and Olsen, 1976). Rules may not actually cause behaviours but be inferred from them (Weick, 1989). Changing agent rules may not affect an agent's behaviours, or behaviours may change without changing the rules (Anderson, 1999). As Anderson points out, causal theories identify aggregate outcomes from causal factors, whereas CAS models can be taken further and used to illuminate and explain aggregate outcomes that emerge from 'structured, evolving interdependencies' at the lower level.

During the process of model construction, modellers take steps to satisfy themselves that they are working as intended. The aim is not really to achieve a verified model, but to perform all the conceivable tests until satisfied that the model is worthy of use as a platform for experimentation, North and Macal (2007, p. 222): "[T]he end result of verification is technically not a verified model, but rather a model that has passed all the verification tests!"

Following model construction and verification testing, the model is ready to be run for experimentation purposes. Davis et al (2007, p. 494) put experimentation "at the heart of the value of using simulation methods... [that adds] the creative and even surprising theoretical contributions that build new theory." They consider four useful ways of conducting simulation experiments:

1) varying parameter settings with a view to exploring the effects on outcomes where this has not been fully explored before;
2) 'unpacking' construct definitions that lack precision, which can have interesting effects on outcomes and facilitate ongoing experiments with a focus on the newly unpacked, constituent parts;
3) varying the assumptions, particularly where they are not explicit in the literature and explore the effects of alternative assumptions that can be expected to produce interesting insights, or raise possibly important questions;
4) adding to the level of sophistication of models iteratively, which is particularly useful when testing new observed system behaviours, and when such a structured approach might expose interactions otherwise obscured.

North and Macal (2007) outline a process for deriving insights from agent model outputs and for presenting them in the form of useful information. To be useful, analysis and presentation needs to be understandable and interesting, and referencing needs to be complete and correct for later replication if required. These steps include:

1) model output recording and logging i.e. documentation of the state of individual agents, aggregate states of groups of agents, and the environment over time;
2) results analysis using traditional statistical analysis techniques, or time-series analysis methods and pattern detection techniques;

3) sensitivity analysis of key parameters i.e. sensitivity to small changes, shocks or errors in the inputs, useful for identifying where to focus efforts, for narrowing down rules and candidates for variables when these are uncertain;
4) exploring behaviours over relevant ranges of inputs and determining desirable inputs, identifying best-worst cases most critical to decision-makers, critical points etc.
5) presenting the results using suitable techniques that facilitate interest and understanding, including characterisation of model outputs over the parameter space e.g. classifying behaviours as stable versus unstable, and the conditions for their emergence, using graphs.

Facilitating model ‘validation’ is the final step in the Davis et al roadmap. The ‘validation’ process has been likened to that in which a “preponderance of evidence is compiled about why the model is a valid one for its purported use” (North and Macal, 2007, p. 13). Some researchers suggest a model should be reasonable, its ‘reasonableness’ a matter of comparing, contrasting and supporting it with the work of other researchers, and of determining its coherence with stylized facts or empirical regularities (Carley, 1996; Dosi et al, 2006; Windrum et al, 2007).

Windrum et al (2007) note that employing empirical evidence to ‘replicate’ sub-regions of the parameter space “could be sufficiently informative” if the chosen set of stylized facts that are modelled is large enough. They argue that this helps to restrict the stochastic processes that might have generated the data that display them. Stylized facts are broad, stable patterns ‘observed’ to emerge from many different sources of empirical data (Kaldor, 1957).

Accumulating evidence to support a model’s match with the ‘real’ target system requires that researchers adopt a realist perspective. A model that survives a battery of such tests for its match with ‘reality’, or that is salvaged through further work, gains credibility and raises confidence in the simulation outcomes (North and Macal, 2007). Here it is a case of achieving validity by degree, rather than of classifying the model as valid or invalid (Law and Kelton, 1991).

However, Ahrweiler and Gilbert (2005) point out by way of example, that in spite of its fame, Schelling’s urban residential segregation model is a doubtful match with the underlying dynamics of the ‘real’ target, due to difficulties in gathering reliable data to support it. They note that questions about peoples’ tolerance levels for residential choices are hypothetical, abstract and likely to elicit biased responses. Unfortunately these authors also point out that from a constructivist perspective, if both target and simulation are constructions (simulation being a ‘second order’ construction), evaluating a simulation is not possible at all without a common ‘reality’.

The way out, according to Ahrweiler and Gilbert (2005), is to infer from the Schelling example that a model that is interesting and well described, in spite of a lack of empirical support, can remain “a fruitful source for theorising and developing new models”. By generating further scientific work the model is considered to satisfy the criterion that it is ‘valid’. From this ‘user community’ perspective, a model is good if it works i.e. contributes to understanding and to building new knowledge. This depends not on how well it fits with ‘observations’, but on whether others are interested in it, and will support it. To that end, model evaluation does not depend on an ‘a priori’ standard, but on the way the research is conducted and described, a view not far removed from that of empirical epistemology (Kertész, 1993).

Stylized facts are still argued to be useful. They can be used to guide model construction, to increase the transparency of a model and thus to inspire critical discussion (Heine et al, 2005; Ahrweiler and Gilbert, 2005). These authors note that they can be used as points of reference to focus discussion on a model’s contribution, without restricting discussion to abstract arguments.

To generate further scientific work, and thereby satisfy the validation criterion from the user community perspective, Carley (2002) suggests the need for:

1) clear statement of the input and output components, internal mechanisms or processes, initial conditions, parameters, boundary conditions, limitations, experimental design, possible biases and number of sample runs;
2) access to archives of model outcomes and software information, for reruns and model comparison by future researchers;
3) flexibility, by means of a suitable toolkit with flexible GUI to allow users to alter parameters and input data etc., and to recode parts of the model.

Carley (2002) notes that for these reasons more recently developed models, because of their accessibility and low cost to run, carry a higher likelihood of ‘validation’.

This approach means that model utility does not require that restrictions be placed on model parameters. Instead, as indicated, sub-regions of the system can be identified and a model developed that is expected to reproduce some relevant aspects. Sub-regions can then be compared with future models using different computational techniques, details and assumptions.

In such cases model evaluation is the domain of subject experts. Here North and Macal, (2007, p. 230) note the need for a special type of person who is “able to understand the purpose of the model, what it is trying to accomplish, and is willing to accept the tradeoffs required between a model that is too detailed and one that has too little detail”.

Carley adds (1996, p. 6): “For computational theories as with most theories, the researchers who test the theory are generally not those who propose the theory. Rather, the computational theory as with non-computational theories may require many different tests, in many different venues. In this sense, validation can become a process of theory verification and extension (Hanneman, 1988). In summary, validation should not be held up as a pre-requisite for the presentation of a computational model and its predictions.”

2.2 CTS

Developing strategic management theory in the context of complexity has given rise to an emergent theory, tentatively, CTS. In relation to traditional planning and learning perspectives, Cunha and Cunha (2006, p. 839) write: “Recently, however, a third paradigm has begun to be explored – one that synthesizes elements of the planning approach and elements of the learning approach... This integration is made possible by the appropriation of knowledge created in the context of complexity, hence its designation as a complexity theory of strategy.”

CTS has roots in three literature streams, 1) research into market dynamism grounded in the Austrian view of economics from Shumpeter to Koppl, 2) research on loose coupling and dynamic capabilities (Teece et al, 1997; Brown and Eisenhardt, 1997; Eisenhardt and Martin, 2000; Rindova and Kotha, 2001), and 3) a theoretical logic about the relationship between simple structures and system performance from the complexity sciences (Kauffman, 1995; Simon, 1966; Axelrod, 1997 etc.).

For application in highly dynamic markets, CTS builds on 1) the critical significance of time and timing for action, 2) the pursuit of evolving, temporary competitive advantages, 3) a change in the nature of dynamic capabilities from detailed routines based on past behaviours to flexible, simple rules for capturing fleeting opportunities based on minimally structured, distributed decision-making systems, 4) opportunism and strategic improvisation, as a means of fitting opportunity execution with changing demands.

This section addresses the aspects of CTS most relevant to this research. It begins with the important, yet often overlooked concept of time. While acknowledging the incompleteness and conceptual imprecision of time, CTS attempts to progress from past mechanistic assumptions toward a discontinuous and heterogeneous perspective of time. Attention then shifts briefly to issues relating to the environment. CTS offers an opportunity-based strategy as the alternative to traditional strategies for highly dynamic environments. There is longer-term consensus on several important attributes of such environments and recent efforts to capture opportunities in terms of flow and change.

Finally, focus shifts to the agents in the system. CTS proposes a move from the pursuit of sustained advantage to evolving, temporary advantages, suggesting minimal organizational structures that facilitate distributed decision-making under constraint, via rules that guide and govern goals and responsibilities. The suggestion for capturing fleeting opportunities is 'strategic improvisation', the result of speedy, sub-optimal, but nevertheless voluntary decision-making, which calls for orientation to dynamic action.

The section concludes with a brief summary of the way forward for CTS, in the context of this research.

2.2.1 Time

In earlier strategic management research, time generally played a subordinated role in the strategic equation, since it was assumed that markets did not change, or change slowly and predictably (Eisenhardt and Sull, 2001). From the mechanistic perspective, time was largely overlooked by the rational, utility maximiser. But strategic decision-making, especially in dynamic markets, is a dynamic task (Farjoun, 2002).

Hence, researchers have become increasingly aware of the importance of time and timing, whether as a crucial factor in the exploitation of opportunities (Sarasvathy et al, 1997), a simple rule for securing temporary competitive advantage (Eisenhardt and Sull, 2001), or a mechanism for directing decision-makers' attention toward continuity or change (Gersick, 1994). The same goes for the timing-performance relationship (Gersick, 1994; Eisenhardt and Brown, 1989; Eisenhardt and Sull, 2001), and for the different dimensions of highly dynamic environments per se (Eisenhardt, 1989a; D'Aveni, 1994). The suggestion is that organizations need to transform vigilance into action and be quick about it (Cunha and Cunha, 2006). In spite of this, most models have neglected time as a variable, treating it implicitly (Butler, 1995), and as might be expected of an emerging theory, our understanding of it is incomplete (Davis et al, 2007).

One dimension of time relates to whether decision-makers regard the future as continuous and dependent on the past, or discontinuous (Crossan et al, 2005; Leybourne, 2006). The continuous perspective points to linearity and therefore implies that decision-makers ought to attempt to extrapolate the future from the past. The discontinuous perspective implies that decision-makers prepare for contingencies. Adopting a recurrent approach of the continuous time perspective is a further option, implying that decision-makers attempt to detect past routines and schemata in order to benefit from cycles – seasons, programmes and so on – and to synchronize their decision-making and actions with them (Leybourne, 2006).

Another dimension relates to how decision-makers perceive the flow of time i.e. whether they distinguish the dominant perspective of time, 'clock-time', from alternative concepts. Bluedorn and Denhardt's (1988, p. 304) definition of clock-time reveals why this is important: Clock time or 'even' time is a time "characterized by divisibility into equalized, cumulating units... openness to unlimited extension and no particular concern for the past, present, and future." Management and decision-making, however, require flexibility and responsiveness to events and discontinuous changes, thereby placing limitations on the efficacy of clock-time (Mintzberg, 1994; Eisenhardt and Brown, 1998).

Synthesising the two perspectives into clock-event-time (Crossan et al, 2005) would be more consistent with management practice, where creative genius, luck and effort can all play a simultaneous role. 'Heterogeneous time reckoning' – including regular, rhythmic opportunity-transitioning and calendar-based deadlines – has been found to lead to improved performance (Clark, 1985; Brown and Eisenhardt, 1997).

A clock-event-time perspective would facilitate both temporal and event-based pacing of decisions and actions, enhancing our understanding of how successful decision-makers choose to persist with certain opportunities and not with others. But a synthesis of time perspectives is considered to be methodologically and practically problematic: methodologically because few measures of time, clock-time or event-time, exist in the first place, and practically, because perspectives of time and treatment of urgency differ among individuals.

It is nevertheless appropriate to acknowledge the relevance of this research to any model or theory of decision-making in CAS, and to show awareness of the mechanistic assumptions regarding the treatment of time that have characterized past models. For CTS, the suggestion is that were decision-makers to search and experiment with opportunities, transition between them and recombine businesses to some sort of pattern or rhythm, based on these perspectives, performance would improve.

2.2.2 Environment

Attributes, variables

A number of different terms and concepts have been used to describe environments that have undergone the type of rapid change described in the previous sections. *Turbulence*, following Emery and Trist (1965), is a reflection of the degree of interconnectedness among the elements of the environment. Richly connected turbulent fields, so-called Type IV environments[30], possess dynamic properties arising not only from interaction among the organizational components but from the environment itself: the 'ground is in motion'.

The wide range of environmental textures and dimensions that followed Emery and Trist's work was reduced by Dess and Beard (1984) to a reasonably parsimonious set: *munificence* (capacity), *dynamism* (stability-instability, turbulence) and *complexity* (homogeneity-heterogeneity, concentration-dispersion).

In munificent environments, organizations can generate resources that see them through more scarce times. So a measure, or reflection, of munificence would be profitability or the rate of growth e.g. in turnover.

In dynamic environments, organizations have consistently been concerned with change associated with uncertainty beyond the level of control of the decision-makers. So absence of pattern and unpredictability might be considered suitable measures of environmental dynamism (Dess and Beard, 1984).

In complex environments, organizations engage in a wider range and diversification of interconnected activities, which they associate with uncertainty and greater information-processing requirements, than decision-makers in simple environments. Siggelkow and Rivkin note (2005, p. 103): "A firm making decisions whose performance effects are independent from each other is said to operate in a simple environment, while a firm whose decisions are highly interdependent is said to operate in a complex environment." A source and measure of complexity might therefore be considered to be the degree of interdependence among the elements that surround agent decision-making[31].

Researchers have attributed other dimensions to the environment besides those mentioned. Sutcliffe and Huber (1998), for example, tested peoples' perceptions of

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[30] The other environments identified by these authors were not classed as turbulent, but as either relatively unchanging (i.e. placid, randomized), somewhat complicated or disturbed, requiring speed and flexibility, but nevertheless stable i.e. not environments that "create significant variance for the organization's themselves" (Emery and Trist, 1965, p. 10).

[31] Although both turbulence and complexity both build on the notion of interconnectedness among the elements in the system, these authors view the former more in terms of speed of change, the latter in terms of breadth of interdependence.

environmental munificence and complexity, adding instability, hostility and controllability to earlier dimensions. Embedded in each of the textures, combinations or environmental characterisations, and inevitably at the centre of researcher interest ever since Emery and Trist (1965), has been the factor of change (D'Aveni, 1994; Teece et al, 1997; Eisenhardt and Martin, 2000). Here distinctions are made between the rate, turbulence and magnitude of change. These have been noted to impact the environment independently. The semiconductor industry, for example, has experienced apparently high rates of change but low turbulence and low magnitude[32], the circuit board industry high rates of all three (Nadkarni and Narayanan, 2007).

One result of the focus on change and dynamism has been to conceptualize environments as consisting of opportunity flows – identifiable and promising flows, but surprising and fleeting ones (Sarasvathy et al, 2003; Davis et al, 2007). Based on this, Davis et al (2007) most recently attempted to capture market dynamism in a computer simulation by dissecting it into four dimensions: velocity (the rate of flow of opportunities), ambiguity (the degree to which features of the environment are difficult to understand), complexity (the number of features of an opportunity) and entropy (the unpredictability of flow patterns, the difference between past and present).

2.2.3 Agents

Agent decision-making

For CTS, when rates of external change exceed those of internal change, focus shifts to temporary advantages that emerge from local agent decision-making and interaction (Brown and Eisenhardt, 1998; McKelvey, 1999). The task strategic decision-makers have in accounting for the unpredictability of nonlinear systems is to establish and modify the direction and boundaries within which effective, improvised, self-organized solutions can evolve, and to place less emphasis on prediction and control (Meyer et al, 1998).

Brown and Eisenhardt (1998) suggest that if evolving, temporary advantage is to emerge from local decision-making and interaction, decisions and actions need to be constrained, outcomes observed, and then the constraints revised. They refer to this as tuning the system, "by altering the constraints, all the while raising or lowering the amount of energy injected

[32] Magnitude of change has been used to describe, or been interpreted as, the scope or size of change, often in conjunction with incremental vs. radical change (Nadkarni and Narayanan, 2007).

into the dissipative structure they are managing" (Anderson, 1999, p. 228)[33]. These researchers suggest constraining agents at the business unit level by implementing a few rules that guide and govern their goals and responsibilities and how they perform.

Brown and Eisenhardt (1998) envisage organizations as 'ecosystems of modular patches' (businesses). They suggest that a high level of local autonomy is required to overcome unresponsiveness due to rigidity when businesses are too large, or to avoid chaos (overlapping of interests and cannibalization) when they are too small. Their call to capture the middle-ground, thereby "[allowing] the ecosystem to stay on the edge of chaos" (p. 229) away from overly ordered and chaotic regimes, is an effort to apply the lessons of Kauffman's NK model to business strategy.

The organization is able to respond to rapid change by ceaselessly recombining its portfolio of business units, thereby generating novelty whilst retaining the best performers. The domain of the business units, the niches they operate in, the way decision-makers make their living, is the context through which strategists are able to shape the emergent nature of the organization. In other words, strategists at the upper hierarchical level, rather than shaping a pattern or building a position, shape the context from which it emerges, by influencing agent rules, or schemata, and hence how they vary, select and retain ideas, initiatives, business modules and so forth (Anderson, 1999; Eisenhardt and Martin, 2000; Eisenhardt and Sull, 2001).

The strategist is perceived as an organizational architect, able to influence the behaviour and interaction of agents relying on the positive evolution of cascades of change (as opposed to prediction and control). The rules for guiding and governing the organization's behaviour are actually intended to enable rather than constrain i.e. to enable versatile and flexible responses at both managerial and organizational levels, rather than act as rigid and rule-bound directives. 'Simple rules' for organizations are intended as a synthesis of strategic intention, managerial foresight and organizational control, providing a balance of freedom and constraint that influences their future shapes (Meyer et al, 1998; Anderson, 1999; Cunha and Cunha, 2006).

Cunha and Cunha, 2006 (p. 843) summarize: "Minimal structures are constituted by a clear strategic intention, an adequate number of simple rules and ample individual freedom. Strategic intention provides agents with a way to determine what strategic direction it makes sense to take and gives control a centrifugal nature, instead of the centripetal conformity

[33] Note that efforts to increase attention, reduce uncertainty, are enhanced by a distributed decision-making process.

enforced by ‘thicker’ structures – be they based on obtrusive direct supervision or unobtrusive cultural commitment.”

The focus on fast changing and dynamic environments which resulted in suggestions that organizations also pursue temporary competitive advantage and develop minimal, distributed, rule-based decision-making structures, has also resulted in propositions that advantages are attainable through other avenues, such as dynamic capabilities and continuous morphing (Teece et al, 1997; Rindova and Kotha, 2001; Mayer, 2006). Dynamic capabilities relate closely to simplicity, simple rules and simple structures. Structural simplicity relates to a flatter hierarchy, with greater autonomy of action at the lower levels. Not having to wait for instructions saves time (Gersick, 1991; Zott, 2003).

The speed of the distributed, centrifugal organization calls for improvisation on the part of agents, and since, following CAS, we cannot step in the same river twice, unavoidably surprise. Actions may be voluntary, but unexpected and therefore not made under optimal conditions, ‘conferring a strategic nature to improvisation’ (Perry, 1991). Crossan et al (2005) distinguish between different types of improvisation in organizations, pointing out for example that uncertainty may be as much at stake when improvising in organizations as time. In their words (Crossan et al, 2005, p. 132): “Even if there is time for it, planning is unlikely to occur, because individuals are frustrated by either too few or too many possible interpretations of events. Instead of planning and then acting, people improvise: they act first and then make retrospective sense of their experience in order to act again.”

In rapidly changing environments and crisis situations, when planning is impossible due to time and unpredictability, ‘full-scale’ improvisation takes place. Individuals then ‘wade into situations’, believing they can recombine their knowledge and ‘make do’, and thereby balance their knowledge and doubt (Weick, 1995).

Agent strategy as opportunity pursuit

For CTS, strategy as the pursuit of opportunities (Appendix A3) is a way of keeping up with dynamic changes (Weick, 1995; Eisenhardt and Martin, 2000; Eisenhardt and Sull, 2001). Agents engage in a type of temporal, guerrilla-type warfare, characterized by opportunism, speed of movement, and rapid loss-cutting. The strategic watchwords are simplicity, organization and timing. Decision-makers are required to jump, even into uncertain situations, where opportunities are considered to be most abundant, and drop them as soon as they fail to meet expectations (Eisenhardt and Sull, 2001). These authors liken this opportunism, or ‘transitioning among opportunities’, to genetic evolution, with the organization's combined products, brand, technology etc. being its unique gene mix, and strategy akin to genetic engineering, a unique set of gene-changing moves.

Eisenhardt describes the behaviour of opportunity-based decision-makers in a 2006 podcast, as one of shaping opportunities rather than discovering them. In this context, strategy is about networking and placing lots of bets, to be an early (not necessarily the first) mover, rather than about the classic models such as key customers and strategic focus.

Strategy is driven by agents who are "vigilant sensors and skilled improvisers, able to cope with local problems as they emerge". Strategy is driven by agents oriented to action rather than analysis. This is action, according to Cunha and Cunha, (2006, p. 845) "grounded on a strong sense of direction provided by a minimal structure."

In spite of the advantages researchers associate with improvisational action, the risk of error is increased, a risk that practitioners of CTS would need to be more comfortable with than other strategists following positioning or resource-based strategies for example. Cunha and Cunha (2006, p. 846): "Even the attitude towards error tends to be different among adepts of both styles: if error is part of the learning journey among people with a learning style that privileges action, it is wrong and humiliating for those with a style that privileges reflection."

2.2.4 Developing CTS

For some time researchers have been pointing the way forward: 1) to the extent that decision-makers do not always act rationally, have limited attention and cannot sense-make (March and Simon, 1958; March and Olsen 1976; Weick, 1995; Gifford, 2003), a model that sufficiently separates process from outcome is required, 2) if the locus of opportunity discovery or creation lies with people, then cognitive psychology (e.g. insights about intentions, perceptions, categorization) is relevant to modelling the process (Dutton and Jackson, 1987; Salgado et al in Augier and March, 2002; Krueger in Acs and Audretsch, 2003), 3) there is a need to extend the framework to the multi-agent case (Siggelkow and Rivkin, 2005; Davis et al, 2007), 4) given that uncertainty and unpredictability preclude expectation, then error and surprise should be treated as features of the opportunity exploitation process, blurring the distinction between environment and agent.

Broadly, CTS attempts to fit strategic management theory with the landscape shaped in Sections 1 to 3 of this Chapter. It addresses strategy in organizations that are innovative, knowledge-based, have looser forms of collaboration and sometimes fluid boundaries, rather than in traditional business corporations that are asset-intensive, vertically integrated, have rigid boundaries and tight control over employees. By embracing the Austrian view of entrepreneurship it helps our hitherto restricted understanding of the business landscape in a manner consistent with the concepts of complexity and emergence. Because it builds on novel concepts, however, its articulation requires further research, hence its designation as ‘simple’ theory.

Developing ‘simple’ theory (with modest constructs, propositions, or empirical grounding, but *some* theoretical understanding of basic processes), as opposed to developing established theory or theory creation is particularly well served by simulation, by ‘exploration and elaboration through computational experimentation’ (Davis et al, 2007). The argument is that simulation actually thrives off lack of precision and incomplete theory in order to be able to provide any insights. Conversely, in the case of well-developed theory, such payoffs are considered fewer and further between and where theory is non-existent, payoffs are beyond reach. The idea is that there should be both sufficient theoretical development and room for improvement, for simulation to be of maximum value.

Central to all modelling research is the trade-off between clarity of expression and precision (typical of formal, quantitative approaches) and power of expression and descriptiveness (typical of qualitative modelling approaches). The next chapter reveals how ABMS manages to occupy the middle ground – a powerful approach that combines the rigour of formal logic with the descriptiveness of the agent paradigm for representing actors and interactions (Moss, 2007; North and Macal, 2007). It ‘shifts out’ the trade-off between rigour and relevance in social simulations (Moss, 2007), as is the case here, where the main challenges are a combination of conceptual imprecision, ambiguous environmental dimensionality and partly-understood agent roles and behaviours. The merit of ABMS, besides being a test bench for the terms and definitions used in the CTS framework, is that it opens a way of implementing aspects of components and systems previously thought impractical (North and Macal, 2007).

2.3 Synthesis

The aims of this review were to establish the context and structure of this research; to identify contributions in the area of strategy that have been informed by the literatures associated with CAS and ABMS; to identify the main methodologies and techniques used by researchers; disclose relevant variables; and to relate, where possible, the academic ideas to business practice.

There have been attempts to better merge strategy and reality – to merge an analytic approach with incessant, temporal and emergent conditions –in part a direct result of perceiving markets to be in ceaseless motion, populated by alert individuals, and of the open, social context of complex, adaptive organizational systems. The environment is regarded as more inclusive, continuous and path-dependent, more interactive and integrated with the notions of structure and evolution, and with the behaviours of the agents in the system.

Markets are Schumpeterian environments, in perpetual disequilibrium due to the replacement of current technologies with new ones, and can be seen as richly connected turbulent fields – generally munificent, dynamic and complex – able to facilitate growth, but liable to change unpredictably. The independent drivers of environmental change encourage their conceptualization as diverse flows of fleeting opportunities.

A number of models have enriched the field including the development of a typology of entrepreneurial opportunities. The creation, discovery and allocation views, based on differing pre-conditions for their existence, can be applied to organizations at different stages in their development, and are therefore better integrated than separated. Some models do blur the distinction between the environment and the agent, between opportunities and choices, suggesting people invent things based on their perceptions, or cast opportunities as the result of interaction and negotiation, rather than as pre-existing. But at some point before their exploitation, opportunities must exist, hence the assertion that the exploitation process itself is sequential.

Recognition of the limitations of decision-makers, and their interconnectedness in turbulent environments, registered an epistemological shift from mechanistic to organic principles i.e. away from disconnected, mechanistic leanings toward integration, uncertainty and complexity. With this there are attempts to integrate phenomena, concepts and variables to address the 'messy side of reality', without necessarily breaking with the past, but by building on it. At the centre is the agent, with an 'awareness of the contingency and provisionality of things', shaping the organization's passage through a willingness to change perceptions and adapt to them, rather than be lulled into a 'false sense of security'.

These profit-oriented decision-making agents are treated as the driving force of market processes. They are surrounded by uncertainty, unaware of what they are ignorant about, and hence, though they may learn, they make errors and are surprised by outcomes. Their individual uncertainty can be better explained via the role of human capital investment, than formerly through irrationality or the risk-bearing assumption.

Though agents are alert and form perceptions of opportunities based on environmental cues, the process is complicated, and therefore best simplified in terms of strategic issue categorization – the proven contention that individuals and organizations categorize issues positive and negative, opportunity and threat, controllable and beyond control. This particular field of inquiry offers rich theory and well-developed methods.

To a large extent, the shifts that took place in how researchers viewed the environment and the behaviour of organizations were the result of technological change and globalization and the effects on time and the interconnectedness of the elements of the system. This affected the mindsets of some strategic management researchers, opening up the field to contributions from other disciplines, notably complexity theorists.

The evidence that organizations exhibit CAS behaviours has fuelled interest in concepts such as improved performance at or near the 'edge of chaos', butterfly effects and emergence from simple origins. Systems are complex because of the number and nature of the elements they consist of. Systems are adaptive if they are able to balance order and disorder over time, and hence co-evolve with their environments. They do this when composed of multiple, unique, related and partially connected agents that follow their own autonomous set of simple rules.

When subjected even to small changes the paths that CAS follow are nonlinear, often highly unpredictable, causing surprise. Although they tend not to return to fixed, cyclical equilibria, their behaviour may be constrained to basins of attraction. Even without any centralized authority they are able to evolve to a critical state, exhibiting novelty and behaviours that adhere to the same power-law driven principles. These insights have produced recommendations that business strategists be more open to trial-and-error learning to repeat their efforts at imitating others' successes, to search for emergent patterns and to abandon the pursuit of limit states.

Explanations that agent behaviour is governed by schemata and can be modelled as fixed or fuzzy rules, that agent actions maintain the system without the need for any central organizing control, offer new perspectives for the field of strategic management. Decision-makers, without being able to forecast outcomes, who may well suffer from limits to attention, can contribute to successful outcomes by pursuing their own goals. Their choices are interdependent, so they co-evolve, shifting their behaviours continuously, poor performers being replaced by random substitutes, recombining according to a power law arrangement.

The study of complex systems that are not purely deterministic, predictable and reversible has required new approaches that go beyond those of 'normal', positivist scientists, toward a science of order creation. It is still regarded as a relatively new approach to science, although its relevance to organizations was clear to the early Austrian school of economists. Order was argued to emerge not because anyone, or any regulatory institution, understands or can orchestrate it, but in a spontaneous manner, 'the result of human action rather than design'.

Without agreement on a definition of complexity or the basic principles of a complexity theory for organizations, different schools of thought and terminological preferences may continue to prevail. But certain characteristics associated with order-creation science are reasonably clear, with important implications for strategic management theory and modelling organizations.

Advances in computer technology are enabling researchers to build on these insights adopting different modelling approaches that focus on the construction and manipulation of the system elements and observation and analysis of outcomes. Flexible modelling of environments and agent schemata is intended to address the interdependencies, hierarchical nature and cognitive limitations of the elements and agents, thereby building on the contributions of March, Simon, Weick, North and Macal and others, in a non-reductionist way.

ABMS is a flexible method of modelling, which allows for 'changing the ingredients' in a manner that avoids the assumptions of homogeneity, agent or data point independence or equilibrium that neglect the individual dynamics and uncertainty indispensable to modelling and theorizing human behaviour. It is not necessary to understand all parts of the system holistically. Instead, attention can be focused on agents locally, assumptions made about their schemata, and variations tested out with fixed or fuzzy rules, by cycling back and forth between inductive and deductive methods. This was previously considered impractical. The discovery of useful and interesting patterns and behaviours using stochastic models may open up avenues for learning where it is not necessary or possible to include all the details, and where much of what is modeled can be approximated.

CTS, built on incomplete conceptualizations of time, highly dynamic environments and opportunistic agents, that together form CAS, represents an ongoing attempt to fit strategic management theory with this landscape. Researchers are therefore pointing to the need for models that sufficiently separate process from outcome; that account for important cognitive aspects of agents; that extend frameworks to the multi-agent case; that treat uncertainty, unpredictability, and hence error and surprise as features of the opportunity exploitation process; and that do not dichotomize environment and agent.

Developing CTS is argued to be well served by ABMS because simulation actually thrives on a lack of theoretical completeness, and because agent-based toolkits are demonstrating their suitability for investigating CAS, for capturing dynamic markets and agents with schemata.

The next chapter addresses more deeply issues of methodology and methods relevant to this research. There it is noted that computational experimentation is better served by adding to, rather than removing, uncertainty. The utility of ABMS is increased by including more parameter switches and more dimensions of uncertainty. The general claim is that computational science models constructed for the purposes of experimentation with social science problems are better measured in terms of evolutionary or post-positivist epistemology than positivist frameworks, because what is needed is a model that supports the exploration of a particular problem, as opposed to an 'image of reality'. For researchers like McKelvey this is the avenue that allows scientists to use the formalized methods likely to produce theories about effective entrepreneurial practices with 'higher truth value'.

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3. METHODOLOGY, METHODS

This chapter briefly considers the research-relevant issues of methodology and then, more extensively, of methods. Methodology is taken to refer to the set of ontological and epistemological assumptions (Prasad, 1997), the form of thought characterising this research, which is important particularly in understanding how the findings are interpreted. Methods are taken to refer to the tools and techniques used here, important for an understanding of how the findings were arrived at (Mir and Watson, 2002). Methodology and methods are therefore addressed in separate sections.

There is a need “to reflect critically on the nature and the limits of our knowledge and understanding... indispensable to a study of complexity” (Cilliers, 2000, p. 32) and a reminder that philosophy makes many potential contributions to this subject area, more toward opening discussion than resolving issues. For this type of research there is avoidance of the selection of a single, hard-wired orientation. As Wickham (1998) points out, some subject areas, such as the natural sciences, are dominated by a single, widely accepted paradigm, a generally accepted theoretical framework for enquiry, whereas others are either multi-paradigm, or at least are not dominated by a single framework.

On epistemological perspectives for simulation, Becker, Niehaves and Klose (2005) state: “The discussion of epistemological questions must, at least presently, be considered as an open issue. For this reason, no theory based on a philosophy of science can be considered as binding for researchers.” The posture adopted for this research fits best with a form of hybrid, social constructivism. For the evaluation of CTS-SIM, although observer and world are blurred, objective knowledge need not be considered impossible. What is considered impossible is to know all the components of CTS-type systems. So the aim is to model aspects of the system, to explore how they might work.

Cutting out parts of the system carries the risk of distortion. However, adopting a ‘user community view’ requires that the outcome prove to be a ‘fruitful source for theorising and developing new models’ (Ahrweiler and Gilbert, 2005). Beyond that, anything goes (von Glasersfeld, 1987). Such an approach accepts that there are possible worlds, but settles for something more modest than the pursuit of truths, or even viabilities.

The aims of the main part of the chapter, Section 3.2, are to describe the *methods* of design and analysis used in the research, to assess their appropriateness, demonstrate an awareness of ethical issues, and clarify the type of research being conducted. The section covers simulation as a research method and outlines the main areas in which strength of method for this research is rooted. These boil down to a focus on the main research problem; to the choices and justification for the approach adopted; to the steps that are taken to ensure the model is adequately described; and to the experimental make-up of this research. A separate subsection is devoted to each of these aspects.

3.1 Methodology

Modellers in the social sciences tend to adopt the approach that theories cannot include all the features of a phenomenon. There is a need for some degree of abstraction, some limitation in scope. So, in line with the Semantic Conception of Theories, it is possible to treat theory, model and phenomena independently, models acting as mediators or bridges between theory and phenomena (Morgan and Morrison, 2000).

It is particularly relevant when constructing and running simulation models to consider the modeller's influence, the perceptions of both subject area and problem domain. The researcher adopts a constructivist position, according to Becker et al (2005), when either subject area or problem domain are, or cannot be, assessed objectively.

These authors suggest that simulation models should refer to a real world issue and describe elements that are part of it. Some researchers also point out that simulations can reflect attempts to *repeat* rather than *represent* abstractions of reality, undermining the distinction between the real and the simulated (Cilliers, 1998; Grandy and Mills, 2004). Hence for these authors simulation models can be basically understood as reconstructions of 'real' issues. Furthermore, since simulations are expressed in a particular modelling language, they are a formalized representation of domain understanding. So, just as the scientist conducting experiments using simulation and claiming objectivity would need to clarify how it is achieved, so would he or she need to clarify the domain understanding of terms and concepts.

In asking what properties a computational model should have in order to answer a research question, Bankes et al (2002) distinguish between the veridical and exploratory model of a system. The first, the typical mirror-world model (see Chapter 2), when applied to open systems problems, "is a flawed mirror, which has the potential to deceive as well as illuminate" (p. 379). However, when surprise is ultimately assured, as is the case in this research, a framework consisting of computational experimentation using an exploratory platform is useful. From this perspective experiments are performed that produce outcomes supportive of the articulation of credible arguments (Bankes et al, 2002).

All that is needed is a model that supports the exploration of a particular problem, not an image of reality, Bankes et al (2002, p. 379): "Thus, an economic model that demonstrates highly efficient market outcomes using agents with very limited reasoning abilities can be used to support an argument that efficient outcomes may be an emergent effect not requiring any particular intelligence or wisdom on the part of the market's participants. A model with more realistically intelligent agents would be less useful to this argument than the clearly unrealistic one with unreasonably stupid agents."

The important point these researchers make is that, rather than attempting to limit uncertainty, computational experimentation is better served by adding to it, by increasing the parameter switches and declaring more dimensions of uncertainty, and thereby increasing the model's utility. The consequence, from a methodological perspective, is that *veridical* (predictive) modelling is biased toward deductive reasoning, hence the preference for validity when measuring its scientific quality. *Exploratory* modelling, on the other hand, is biased toward inductive and abductive logic[34], sometimes argued to be measured in terms of falsifiability and reproducibility, validation then applying to the arguments based on model outcomes rather than the model itself (Popper, 1972).

CTS-SIM: methodological position

Insofar as this research 'belongs' to the field of social science, it is not dominated by a single, generally accepted theoretical paradigm[35]. Rooted as it is in the subject area of strategic management, which emphasises both realist and constructivist frameworks, it rejects extreme views and explicitly recognizes the contingent nature of organizational systems. From a complexity perspective, whilst care is taken to avoid claims of completeness or determinism, there is still room in the literature for authors to contemplate the degree to which their orientations should be considered as a form of hybrid constructivism vis-à-vis post-positivism. Either way, these philosophical postures achieve a reasonable fit, it seems, with the methodological *bias* toward an inductive and abductive

[34] The status of abductive reasoning (a form of reasoning backwards to explain the cause of a surprising outcome, for example), is still controversial (Bouissac, 1998).

[35] The debate about paradigm commensurability – whether paradigm proliferation or a dominant paradigm constitutes a proper form of inquiry – is not addressed here.

logic of exploratory modelling, and with the analytical and ontological adequacy espoused by the Semantic Conception of Theories.

For this research, my role as researcher can hardly be excluded, given the framing of the research questions and the research method adopted. While it is conceivable to be impartial and detached, it is less likely that the process of model construction can be claimed to be value-neutral (Mir and Watson, 2001). Hence, for the rest of this thesis, I give regular account of this research in the first person, to avoid imbuing it with an entirely objective character[36]. I do so acknowledging that phenomena exist, that agents pursue payoffs (e.g. cash, debts), but without the mirror-world assumption.

Fitting this research, however, with a form of hybrid, social constructivism, enables a perspective that accepts there are possible worlds, but that settles for something more modest even than the pursuit of viabilities (let alone truths). It builds on the adoption of the 'user community view' and follows von Glasersfeld's 'anything goes, provided it works' approach. By adopting a methodological perspective based on exploratory modelling, biased toward inductive and abductive logic, I need not eschew making sense of a possible world. However, without it being possible to know all the components of CTS systems, I construct the model with the intention of capturing aspects of them, and of using 'If A, then B' propositions to consider how they might work.

So the position I take in this research accepts, as do most complexity researchers, that objective knowledge may not be impossible, even though observer and world are blurred. By not adopting a hard-wired methodological position, and favouring a heuristics-based epistemology, simulation of 'observed' phenomena is possible, while permitting a degree of ambiguity and interpretation.

From this perspective, ABMS allows me to develop CTS through modelling – to strive for plausible, possibly more parsimonious contributions to our understanding of opportunity-based strategies in highly dynamic markets. It permits me to address the 'sweet spot' between theory-creating and theory-testing research. The expectation is that CTS-SIM can function as a source of knowledge and as an instrument of investigation thereby bridging CTS with possible 'real' worlds. As such the model can serve to narrow the gap between rich case-study and simplified traditional modelling.

[36] A potential disadvantage of writing in the first person is that emphasising or repeating a point for clarification can seem contrite to the reader.

3.2 Methods

Balogun et al (2003, p. 197) point out the "increasingly disparate research paradigms now being used to understand strategizing and other management issues" and argue for complimentary methods that offer more 'breadth and flexibility'. Their research focuses on ethnographic approaches and how researchers engage with participants, but the broader message is that there cannot be significant advances in research without re-conceptualizing frequently taken-for-granted assumptions about the way to conduct it.

These authors note the need for proximity to the strategists and organizations themselves, the need to investigate the actual context and details of the phenomena. They also note the conflicts that result from realistic limitations on scope, and of overcoming equilibrium assumptions and assumptions commonly associated with cross-sectional data[37]. These difficulties are accompanied by the growing number of alternative theoretical, methodological and philosophical approaches to choose from and the challenge of distinguishing clearly between them, which hampers thoughts on how data are best collected and interpreted. Balogun et al (2003) show awareness, however, of the advantages associated with this pluralism, the flexibility it allows researchers in strategy in applying different methods and the potential it offers for cross-disciplinary exchange.

How to develop emerging theories in the field of management, the focus of this research, has been the subject of researcher interest for some time. There are compelling reasons to conduct such research through multiple-case studies. They offer potential for the discovery of cross-case patterns in an iterative process going from data to theory (Eisenhardt, 1989b). A criticism of case based studies is that they are not, but should be, representative of some population. This has been dismissed on the grounds that cases can be legitimately selected for theory development if they are "particularly suitable for illuminating and extending relationships and logic among constructs", and not for any other reason (Eisenhardt and Graebner, 2007, p. 27).

Single cases can be very powerful too, even given their more obvious weaknesses of low sample size and non-representativeness. Siggelkow (2007) uses the analogy of discovering a talking pig to illustrate the potential strength of the single case, and the rare medical case of Phineas Gage[38] as an example of a useful single-case study. Nevertheless, given the extremely low probability of such a research result, the need to "cut through idiosyncrasies

[37] Li (2000), for example, notes that a cross-sectional approach does allow for research into a large number of firms at low cost, but that it may fail to identify the causal relationships between variables.
[38] Case refers to a freak workplace accident resulting in damage to the frontal lobes of a construction worker's brain, enabling medical researchers to make inferences about functions of the brain.

and unearth similarities across cases" (Siggelkow, 2007, p. 21) in order to contribute toward theory seems obvious.

Even multiple cross-sectional case-studies generally fail to detect the true nature of causal relationships. Rich, longitudinal case studies, however, are an alternative approach. They have the potential to overcome some of the weaknesses of ignoring the role of dynamic processes in organizations, such as path dependency and self-organization. However, besides their own limitations, including those related to sample size, they are impractical for research of this nature, where financial and human resources are capped in some respects.

Nevertheless, these methods are important in understanding the tools, techniques and methodologies arrived at for this research. They are important because, even though the methods used here are not case based, the research question, and the relevance and utility of the model, depend significantly on case based theory and insights. A model guided by characteristics based on single case 'observations' that are revelatory or unusual, or that benefits from other methods where researchers were able to exploit special situations or unusual access, facilitates critical discussion (Ahrweiler and Gilbert, 2005).

3.2.1 Modelling and simulation

Axelrod and Tesfatsion (2008) note that simulation uses deductive methods, as does theory building, and inductive methods, as does experimental science. But it uses them differently. First, deduction is used to construct a model of a specific target based on certain assumptions, rather than to prove a general theorem. Then induction is used to search for patterns by generating data for observation and analysis through controlled computational experimentation, as opposed to collecting data through observation or direct measurement.

For this research deductive methods are used to define and quantify the drivers of highly dynamic environments and significant opportunity-transitioning behaviours based on explicitly stated assumptions. Inductive methods are then used during the experimental phase when the outcomes of running extensive simulations using CTS-SIM are observed, analysed and interpreted. These processes are guided by the main goals and research question.

Defining and quantifying the environmental drivers and agent behaviours using deductive methods is a step toward understanding their roles and effects, where observing them in organizations can be difficult. It is only necessary to use a few indicators for this, and to resort to assumptions and approximations for the rest. Ahrweiler and Gilbert (2005) note that, with reference to evaluating the Schelling model of urban residential segregation:

"Asking residents how many people of the other colour they would be tolerant of is also an exercise fraught with difficulty: the question is hypothetical and abstract... We can just use some indicators to measure the consequences of learning and assume that learning has taken place. In science simulations, the lack of observability of significant features is one of the prime motivations for carrying out a simulation in the first place."

The key in many agent-based simulations, and in this one, is how the selectable and controllable micro-level drivers influence macro-level, emergent system behaviours. Schelling's urban residential segregation model, for example, shows differently shaded agents following local rules that are considered to govern neighbourhood satisfaction. In that model it is the patterns (clusters) that develop after a number of generations that are of most interest. In CTS-SIM it is the changes in environmental dynamism and munificence and the performance of the agents that are most interest, outcomes shaped by 'local' drivers and behaviours.

For Davis et al (2007), the strength of simulation as a method is rooted in the:

1) *Research question*: how well it is grounded in, and assimilated with, the relevant literature, and whether or not it addresses a substantive gap or question;
2) *Approach*: the modeller's justification for choices that relate to, for example, the levels of abstraction, structure and determinism;
3) *Description*: how well it is conveyed, which includes clear definition of the terms, measures and constructs employed, and the theoretical logic i.e. assumptions and logical flow with the help of diagrams and flowcharts etc. (Rudolph and Repenning, 2002).
4) *Experimental make-up*: how systematically it is conducted and described, the supportive role of statistics, choice of numbers and lengths of simulation runs, which is analogous to sampling issues and confidence levels central to statistical analysis (Law and Kelton, 1991).

For this research, therefore, strength of method is rooted in a focus on the main research problem, that of illuminating core dynamics in the opportunity-transitioning process in highly dynamic environments, thus far elusive using traditional methods alone, yet of particular interest to researchers. It is also rooted in the choices of approach and their justification (Section 3.2.2), in how well the model is conveyed (Sections 3.2.3 and 3.2.5), and in the experimental make-up of this research (Section 3.2.4).

3.2.2 CTS-SIM: approach

Choosing ABMS for this research is based on the evidence researchers have assembled in its favour, in particular the potential for addressing some of the uncertainty and unpredictability inherent in CTS systems and of naturally representing decision-makers as agents. To the extent that agent interactions are inherent to the problem, and neither the environment nor strategic decision-makers can really be conceptualized and formalized by means of a single agent, I opt for a multi-agent approach.

From a social science perspective an agent-based approach helps to avoid traditional, restrictive assumptions, while joining the challenge to top-down approaches to studying complex systems. It facilitates the expression and representation of large amounts of data and knowledge about highly dynamic environments and opportunity-transitioning behaviours; it permits more aggressive experimentation; and it justifies the expectation that dynamics of interest and use to other researchers will emerge.

Another important consideration is that the model, if it is not to be isolated, should be flexible and extensible enough to be useful to future research if possible. This is important, given that the focus of this research is on just a part of the process of opportunity pursuit (see shaded area of the Intentions model in Fig. 2.1). Using a recognized agent toolkit is a way of facilitating this. Model flexibility and extensibility have the twin benefits of enabling the user to ‘change the ingredients’ of the existing version while also serving as a platform that can digest future inputs (e.g. factors affecting perception formation and agent interactions). Over time this enables ongoing, meaningful work and can therefore complement traditional approaches.

The aims for developing CTS theory do not fit with an entirely structured approach, so I follow structured approaches where possible and adopt customized ones where necessary. I follow the broad structure of the Davis et al (2007) roadmap for conducting experimentation using simulation, but adopt a flexible, pragmatic approach to detailed construction using an ABMS toolkit. That way the research is consistent with a number of current observations about how to conduct experimentation using simulation, while being sufficiently flexible to address the non-deterministic nature of CTS systems by integrating controllable behavioural drivers, without having to compromise with unwanted constraints (e.g. agent location, homogeneity).

Simple beginnings, extensions and elaborations

This research is faced, as is most simulation research, with the necessity to shear away aspects of the system and complexity, in order to focus on key behaviours. This can come at a possible cost to its utility. This is normal, given that the purpose is usually to understand or represent an aspect of the target system of interest. Some researchers may criticise a model for not ‘sufficiently capturing the target’. However, a greater evil seems to be that of assumptions failing to surface at all, which is more common in other methods (Morgan and Morrison, 1999; North and Macal, 2007). Nevertheless, as these researchers point out, although CTS-SIM is less complex than CTS-type systems, the goal is that it lead to some improved understanding of how the system, or part of it, functions, or might function.

I adopt a mixed approach, KISS and KIDS. CTS-type environments and organizations are dominated by complex phenomena and there is no reason to expect a very simple, elegant model to be particularly useful (Edmonds and Moss, 2005). There is nevertheless a trade-off between what is descriptively adequate versus what is practical, particularly as a one-stop modeller. To begin with, therefore, I construct just the environment. This is a reasonably simple start, partly intended to engender confidence in the process. Davis et al, 2007 (p. 494): “[It] is often effective to begin with a simple computational representation in order to build reader intuition and confidence in the simulation.”

The initial expectation is that conceptualizing the CTS environment as consisting of opportunity flows and change will permit some control over the behaviour of the environment (dynamism, munificence etc.) via the chosen drivers. This initial part of the construction process produces a rich environment, externally driven from the bottom up. Despite calls for it, ‘unpacking’ the environment in this way, with a view to studying strategy in highly dynamic markets, has not been done before.

Thereafter, as agents are inserted into the environment, model sophistication increases. Generally, the fewer the variables and mechanisms, the easier it is to assess the contribution each makes to the overall results. However, excessive abstraction can make it difficult to relate the CTS-SIM agents to entrepreneur-managers out there. So, while the underlying aim is to ensure that fundamental variables are not obscured, it is also of most interest and use to explore and test, in combination, the variables considered to play a significant role in the process. Design and verification time therefore increase, extensive simulation runs are required, and the interpretation of outcomes is more challenging.

The overall expectation is that populating the environment with agents that form their own perceptions and conform to certain behaviours, within organizational constraints, will facilitate control over important aspects of individual opportunism. The steps taken toward this are incremental and guided throughout by the main research question.

Choice of toolkit

The advantages of using a dedicated ABMS toolkit for this research outweighed the alternatives considered. Several toolkits have strong visual orientations, can meet the challenges of managing large amounts of data and complexity at low cost, and also offer the flexibility and scalability to function as laboratories for current and future model execution.

NetLogo was one of the survivors that made it to an initial test phase. It is currently available at no cost, has the support mechanisms to function as expected, being written in Java (which aids its portability and compatibility). It is also recommended by researchers for its ease of application, Wilensky and Rand, 2007: "[Low-threshold] languages and toolkits are designed to be simple enough so that model authors need not be general-purpose programmers, yet can faithfully implement their models." Gilbert has also expressed preference for ABMS using NetLogo, for its flexibility and ability to facilitate relatively rich models at low cost (Manzo, 2008), and North and Macal (2007) regard the package as a good choice other than for large-scale development.

NetLogo can be viewed as a 'world' inhabited by various types of agents and variables (Wilensky, 1999). Agents can be active, passive, inert or mobile. In the version used (3.1.5) there are four types of agent, although CTS-SIM uses only three: turtles, patches, and the observer. Turtles and patches occupy coordinates on a two-dimensional grid made up of square patches. Turtles can be mobile, though this version of CTS-SIM does not avail itself of this capability. Both turtles and patches have locations and identities and are able to follow instructions simultaneously whilst performing their own individual activities, as do their human counterparts. The observer 'oversees the world' and can, in some models, be used to command the patches or turtles (Wilensky, 1999).

In NetLogo, variables can be turtle or patch variables i.e. with values specific to each turtle or patch. Or they can be global variables, in which case there is only one value accessible to all agents. Variables are treated as places to store values e.g. numbers, colours.

These features make NetLogo attractive for modelling organizational behaviour, especially for this research. In this version of CTS-SIM, patches are used to represent opportunities, with their values being driven exogenously by patch variables. Turtles are used to represent the individual, distributed decision-making agents, and their heterogeneous behaviours are managed by the turtle variables. The observer is used to represent the leadership of the virtual 'organization of agents', global variables being used when one value needs to be accessed by all the turtles (decision-makers). So, to model distributed decision-making behaviour in CTS-type systems, turtles are to perceive, orchestrate and respond to changes on the opportunity patches. To model organizational leadership, the observer does none of these things, and is only able to lift or impose constraints on the overall number of opportunities seized and abandoned.

NetLogo was pitted against two other competing toolkits in particular: AnyLogic and SimSesam. Parts of CTS-SIM were coded in all three. I persevered with NetLogo[39] partly because of its intuitive appeal and reasonably well-maintained supporting documentation. This made it easier to discover and assess features expected to be useful during the verification and experimentation phases.

CTS-SIM abstractions

CTS-SIM focuses on two concepts – an environment driven by opportunity flows and change and agents that transition among them. These guide choices about the elements needed for a useful model. The environment and behaviours of the agents are represented by a select few variables for flows and change and for opportunism respectively, while suppressing most other aspects. Given the complexity of CAS, scientific models often simplify and focus on relationships between limited numbers of variables. It is impossible to capture all the variables of a CTS-type system.

The idea behind CTS-SIM for the longer term is for users to explore and elaborate CTS and to enable the generation of large amounts of data without it being necessary to understand all the parts of the system. Instead, it should be possible to focus on parts of the environment and on certain selected agent behaviours, to vary assumptions about these, and to test them out with fixed or fuzzy rules – and hence cycle back and forth between inductive and deductive methods. This would represent a continuation of the essential experimental tradition of ‘effective science’ and support the shift from equilibrium-based to order-creation science.

So CTS-SIM is to approximate much of the detail of CTS systems. Windrum et al (2007, 2.2): “Due to the impossibility of knowing the ‘true’ model of the world, we can think of the [real-world data generating process] as a very complicated, multi-parameter, stochastic process that governs the generation of a unique realisation that we can actually observe. The

[39] During most of the research phase NetLogo 3.1.5 was the current version. NetLogo 4.0 became available towards the end of construction of CTS-SIM, and although converting to 4.0 was straightforward, running CTS-SIM was slowed, so the experiments were completed using 3.1.5.

goal of the modeller is to provide a sufficiently good ‘approximation’ of the [real-world data generating process] in his/her model.”

To these ends, the external drivers of the CTS-SIM environment are themselves abstractions, understood to incorporate all external factors (technological, political, economic etc.) including competition. The model is limited to representing one organizational entity consisting of agents working toward a common goal of accumulating payoffs. It plays down the role of learning, negotiating, forming and dissolving relationships that inform the process of perception formation, and it abstracts away from the cognitive processes that shape behavioural alteration.

Each is a useful abstraction. Together they need not be considered excessive, as more detail is not crucial for the problem at hand. Attempting to capture more detail can become unnecessarily complicated, if not elusive. As it turns out, these abstractions, at least for some researchers, might be sufficient reason to classify this version of CTS-SIM as a proto agent-based simulation, rather than an ABM. Their reasons might include the fact that there are no rules to change the rules (e.g. Casti, 1997), or because in CTS-SIM turtles do not bother to distinguish each other’s traits, and boundaries between them are flexible (North and Macal, 2008). North and Macal refer to such agents as proto agents, if such characteristics can be added easily without having to modify the structure of the model (which would be the case for CTS-SIM).

In the sections that follow I outline the steps taken in this research following Davis et al’s 2007 roadmap for theory development using simulation: construction and verification, experimentation and model evaluation. There is consensus in the literature that most simulation research does not follow these steps sequentially, though it is practical to present them this way.

3.2.3 CTS-SIM: construction and verification

Model construction involves operationalizing the theoretical constructs, building the necessary algorithms (i.e. coding the selected rules and distributions through sequences of instructions), and specifying the important assumptions. Verification refers to operational efficacy i.e. that the model contains no errors, oversights or bugs (North and Macal, 2007).

Operationalization of the terms and constructs is aimed at their clear definition and quantification i.e. establishing parameter values and ranges[40]. The intention when writing the software code is to construct computational algorithms that reflect the logic underlying the theory. This is a point at which both the advantage and disadvantage of a structured approach vis-à-vis a customized approach is evident, a standardized program being mature but possibly overly constraining (Rivkin, 2001).

1. CTS-SIM construction

To develop CTS theory, what is to be modelled is the construction of a highly dynamic environment and agents that transition flexibly within it, plus a facility to constrain the freedom of the distributed decision-makers. Also such constraints should be manageable. This is akin to managing the energy injected into a dissipative structure.

CTS-SIM environment

The first objective of the construction phase of the model is therefore the deconstruction of the environment into dimensions based on opportunity flows and change. This is to be achieved through defining and quantifying variables that drive the frequency and duration of opportunities, and the speed and direction of change. There is no direct attempt to capture aggregate behaviours of the environment i.e. dynamism and munificence. The expectation is that behaviour of the environment as a whole can be observed and explained as it emerges, from the bottom up.

Bearing in mind that the model strives for utility and to interest other researchers, construction of the environment is guided by the observations of previous researchers and uses important characteristics as reference points to inspire critical discussion. So the aim here is to construct an environment consisting of a large and diverse set of existing opportunities, driven externally by continuous, stochastic flows of transience and change, which gives rise to nonlinear path dependencies due to their interaction and interdependence.

CTS-SIM agents

The follow-up objective of construction is to populate the environment with active, decision-making agents (turtles) that try to perform successfully by accumulating payoffs for their decisions and actions. This is to be achieved by defining and quantifying the variables for important transitioning behaviours, that is, the heterogeneous perceptions, drive, persistence etc. of the decision-makers. Therefore, just as the drivers of the environment are

[40] A parameter is a single measure that possesses a number, or range, of possible values, as opposed to a multidimensional measure (Davis et al, 2007).

managed through the patch variables, the behaviours of the decision-makers are managed through the turtle variables. Again, just as there is no attempt to capture aggregate dynamism and munificence of the environment, there is no attempt to capture the performance of the 'organization of agents'. Instead the expectation is that this can also be observed and explained as it emerges.

Since CTS-SIM is to target the latter part of the process of opportunity pursuit as envisaged in the Intentions Model, construction begins at the point at which the decision-making agents form their opportunity perceptions (whether the outcome of a process of discovery, creation or allocation) i.e. the point at which the thresholds for desirability, feasibility and propensity to act (or desire for control) have been surpassed. Agents then act on their perceptions, seize and abandon opportunities, and are credited with payoffs, a process which is repeated for the duration of the simulation run.

In programming the active decision-makers in CTS-SIM, I follow North and Macal's pragmatic view of agents, which fits with their notion of simple 'proto agents'. By endowing them with fuzzy decision-making capabilities, they are capable of making different decisions in similar situations. So they are active and heterogeneous in nature.

Another main objective of model construction relates to the leadership of the organization of agents and a need for it to control the degree of freedom of the decision-making agents. For this, the 'observer' facility enables limits to be imposed on the number of opportunities that can be seized or abandoned at a time. The decision-making agents, like their human counterparts in organizations, are therefore to be autonomous in terms of their perception formation, but only autonomous in terms of their decision-making, to the degree permitted by the top level. This way agents not only give CTS-SIM the 'additional gear' over alternative modelling and simulation methods, but also over other agent-based models of organizational behaviour, since 'conditional' autonomy more closely reflects the behaviour of people within organizations.

Key model characteristics

Building the model around a number of broad, stylized facts is based on the expectation that this will help to facilitate critical discussion. This means that the modelled environment is to consist of a large and diverse set of existing opportunities (i.e. potentials), to be externally driven by interdependent, continuous, stochastic flows and change. The expectation is that interactions among the interdependent elements will influence environmental dynamism and munificence and give rise to complex, nonlinear and uncertain path dependencies.

A further, longer list of stylized facts relating to the behaviours and strategies of CTS decision-makers and leaders means that the modelled environment must be inhabited by many, payoff-oriented agents that tackle problems at the local level. These opportunists can organize strategic issues into categories, but form their own imperfect perceptions and are able to act ceaselessly, promptly and flexibly on them. Their decisions should be shaped by their own alertness and willingness to act, while their actions take place within organizational constraints, hence at least approximating a simply structured organization.

Opportunities should also be experienced by the agents as both superabundant and discontinuous, and cause surprise and error. This mixture of ingredients should not prevent either success or failure from emerging. Instead it should facilitate both outcomes, driven somehow internally, externally and as a result of chance.

RPX framework

The RPX framework[41] is used to assist with conveying model characteristics, environmental drivers and chosen agent behaviours. The framework illuminates core dynamics of opportunity-transitioning in highly dynamic environments and serves as a simple platform to facilitate ease of understanding. It is a starting point for model construction and not intended, or able, to capture time or flows or represent all of the characteristics that guide model construction. Once coded, however, NetLogo ‘breathes life’ into it.

The RPX framework is aided by flowcharts that convey the main processes involved. Flowcharts are able to show some of the feedback loops between the micro-level variables and macro-level aggregate behaviours. These processes are useful for drawing out important assumptions, which are carefully documented. They are an issue both of scope and simplification.

2. CTS-SIM: verification

An advantage of NetLogo is the facilities it offers for verification testing. Monitoring, debugging, tracking of changes in model specifications, parameter sweeping etc., all play their role in the process of checking the functionality of CTS-SIM. Each of these provides an added measure of reassurance that the model functions as intended, and each ultimately contributes to an increase in the level of confidence in the interpretation of the simulation outcomes.

[41] Recall from Chapter 1 that the RPX framework gets its name from the integration in this research of the three different perspectives of opportunity pursuit: ‘realistic/potential’, R, ‘perceived’, P, and ‘exploited’, X, elaborated upon in Chapters 4 and 5.

Developing the constructs and coding CTS-SIM turned out to be one of the most challenging and time consuming parts of the research process. Once the model was ready for experimentation (technically speaking, not a point at which the model can be considered verified, but one at which the model has passed all the tests) it was possible to cycle back and forth using induction and deduction, avoiding many of the difficulties strategic management researchers often experience at this stage i.e. following data collection.

3.2.4 CTS-SIM: experimentation

In this research, opportunity flows and change are ‘unpacked’ into four environmental drivers, and the parameter settings for the chosen drivers are varied with a view to exploring their effects on dynamism and munificence, this not having been fully explored before (Experiments 1 and 2). Opportunity-transitioning is also ‘unpacked’ into four agent behaviours that are varied with a view to exploring their effects on performance, this not having been fully explored in this way either (Experiment 4). The model is extended to test agent behaviours expected to expose patterns not revealed in the earlier experiments (Experiments 5 and 6). Where guidance from the literature is lacking, assumptions are made, and tests of the sensitivity to variations in those assumptions are threaded into the above experiments. Also, where there is the likelihood of interesting insights that relate to the main problem, or of the opportunity to open up questions for future research, follow-up experiments are conducted.

Therefore, although experimentation is systematic and chiefly problem driven, it is also partly speculative and partly the result of efforts that Weick (1989) terms ‘disciplined imagination’. A *combination* of systematic simulation experimentation and disciplined imagination has the potential to address the features of CAS, where other methods that also employ disciplined imagination (e.g. systematic thought experiments) are more likely to fail (Weick, 1989; Davis et al, 2007; North and Macal 2007).

In brief, the main experiments are:

- Experiment #1: Exploring environmental behaviour by varying the parameter settings of the drivers *holistically*.
- Experiment #2: Unpacking and investigating the four environmental drivers by varying the parameter settings *individually*.
- Experiment #3: Conducting a search for tipping points, thresholds for dynamism and munificence, again varying parameter settings.

- Experiment #4: Exploring the effects on aggregate performance of agent *conviction*, by varying the parameter settings.
- Experiment #5: Exploring the effects on aggregate performance of agent *tolerance thresholds*, by varying the underlying assumptions.
- Experiment #6: Exploring the effects on aggregate performance of model extensions (i.e. organizational delays, agent decision-making freedom) by adding further detail to CTS-SIM.

Fig. 3.1 below fits this approach to experimentation with Shane and Eckhardt's model.

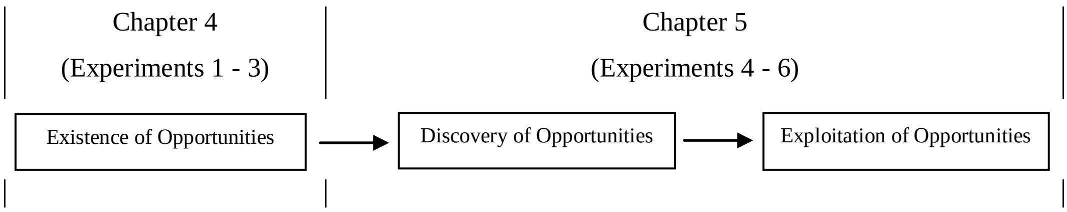

Fig. 3.1. Experimentation following the Direction of the Entrepreneurial Process (see Chapter 2)

During the experimentation with CTS-SIM, I follow North and Macal (2007) in deriving insights from the above outputs and for presenting them in the form of useful information. Documentation of the experiments (using NetLogo's BehaviorSpace facility), the data (Excel 2007) and their observation and analysis (using NetLogo graphs and descriptive statistical analysis supported by Excel 2007) are conveyed in as simple and interesting a form as possible.

3.2.5 CTS-SIM: model evaluation

Although it is the final step in Davis et al's roadmap, validating models is usually a consideration throughout the process of simulation research, as it is with this research.

Given the methodological perspective I follow, the aim is to develop CTS-SIM as 'a fruitful source for theorising and developing new models'. This means that model construction is guided by a number of stylized facts from empirical and case-based observations. The intention here is to explain the CTS-SIM environment taking four behavioural regularities explicitly on board and expecting a further two to emerge from the bottom up, and thereafter to explain agent behaviour taking numerous further stylized facts on board and expecting more to emerge.

Model evaluation is also to rely on careful description and documentation throughout the construction, verification and experimentation phases. If carefully described and explained, CTS-SIM can be more sensitive to the concerns of critical realists and hybrid constructivists when addressing strategic management, and do so while continuing the essential tradition of effective experimental science.

Careful description of CTS-SIM is to address the environmental drivers, the emergent aggregate behaviours of interest, the agent opportunity-transitioning behaviours and the performance of the 'organization' of agents. It is also to cover the parameters and ranges of each variable, the causal relationships between them, the specification of fundamental assumptions, the design of each experiment, numbers of simulation runs and their lengths. All model outcomes are to be archived and software information documented, enabling future reruns and model comparison.

My approach toward facilitating overall model evaluation also includes justification for using ABMS and NetLogo. The bottom-up features of CTS-SIM, combined with the computational rigour of simulation, are expected to squeeze out any hidden or faulty assumptions relating to the area of focus that often escape other research techniques.

Finally, CTS-SIM is compared, where useful and relevant, with a concurrently developed model that studies the relationship between organizational structure and performance in highly dynamic markets (Davis et al, 2007).

Overall, as researchers suggest, the result is not expected to be a 'valid' model. What is expected is an 'explicit' model, Epstein (2008, 1.5): "In *explicit* models, assumptions are laid out in detail, so we can study exactly what they entail... By writing explicit models, you let others replicate your results."

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4. CTS-SIM: ENVIRONMENTAL DYNAMICS

"In those days there were no computers, so he really had to use his brain and think."
Astrophysicist (on the research efforts of colleague, Fred Hoyle)

The structure of this chapter follows the Davis et al roadmap for theory development using simulation:

Section 4.1: Questions addressed in this chapter
Section 4.2: Construction and verification of the CTS-SIM environment
Section 4.3: Experimentation with CTS-SIM.
Section 4.4: Facilitation of evaluation of the CTS-SIM environment.

This structure is a very rough reflection of how the research was conducted. In fitting with a hybrid constructivist epistemology, the nature and framing of the research questions (and hence possible solutions) were partially and inevitably preconceived. Although this roadmap may suggest otherwise, the process was often messy, there being no systematic protocol to be followed in the hope of eliminating all biases from the process. Also, steps were taken toward facilitation of model evaluation throughout the construction and experimentation process, not simply thereafter as it may appear.

The chapter introduces the main RPX framework (Section 4.2). The framework is developed further in the next chapter to account for the decision-making agents and organizational leadership. This establishes a platform to which components can be added, and from which a more coherent perspective of the target CAS emerges.

4.1 Research questions

The main question I pursue in this chapter is *'How do the external drivers of the CTS-SIM environment impact its emergent behaviour in terms of dynamism and munificence?'* Outcomes of the above simulations inform the ongoing experiments. This is the investigation of some of the causal mechanisms that drive CTS-type environments, expected to lay the foundation for illumination of the processes and mechanisms that characterise opportunity-transitioning in the next chapter. It gives rise to three specific questions addressed in this chapter:

1) What variables and attributes are significant and important for an interesting and useful representation of stylized CTS environments?
2) How do the chosen variables affect the exogenous CTS-SIM environment?
3) How sensitive is the behaviour of the CTS-SIM environment to the important model assumptions?

To investigate these, I set out to construct a rich CTS-SIM environment based on important characteristics of CTS environments, one that builds on previous research, but in a new framework that permits more aggressive experimentation. Investigating the behaviour of the environment supports the overall aim of the research. A further aim is to address the difficulty traditional research methods have in capturing uncertainty and the effects of complexity and change as they unfold over time. The expectation, as indicated, is that attempting to capture change and uncertainty is more plausible when the variables can be controlled and manipulated using computers, because the amount of data generated simply becomes unwieldy for alternative methods.

This approach promises to be a practical way of capturing relevant state-spaces, as well as offering strong potential for making parsimonious, plausible and supportive theoretical contributions. The intention is to construct a viable not a perfect environment. Also, not focussing solely on the enacted environment is an integrative approach. Constructing an exogenously driven environment that is opportunity-based permits me to temporarily overlook, and therefore avoid at this point making assumptions about, the behaviours and strategies of the people that operate within it. Once it is possible to observe and control (or at least influence) the emergent environmental behaviours of interest – environmental dynamism and munificence – it will be possible to move on to the heterogeneous strategic behaviours of the decision-making agents.

I conduct three batches of experiments. In Experiment #1, I test the *combined* behaviours of the chosen variables for flow and change by varying their parameter settings and observing their effects on the aggregate behaviours (dynamism, munificence and complexity) of the environment, and over time, this not having been done before. This is the search for longitudinal, aggregated environmental patterns in the absence of a central authority.

In Experiment #2, I test the effects of the chosen variables on the exogenous environment *individually*. Again I interpret the outcomes in terms of dynamism, munificence and complexity at each level (individual, aggregate and cumulative), with the expectation that because opportunity flows and change have not been explicitly unpacked in this manner, interesting effects on outcomes may be forthcoming and raise interesting questions for future research. I follow this up by examining the sensitivity of the outcomes to the important assumptions. So the intention is not only to understand the causal behaviour of the drivers, but also the behaviours of all the drivers in unison, a potentially more useful way of modelling CTS-type environments.

In Experiment #3 I conduct an *open search* for extreme behaviours, tipping points or thresholds that may reveal surprises or signal the need for further pursuit, again varying the parameter settings for flow and change and observing patterns at the emergent aggregate and cumulative levels, a task for which CTS-SIM is predestined.

4.2 Construction and verification

For this research 'growing' a system with the characteristics of 'real' CTS-type systems is as much an achievement as the simulation outcomes it produces. The relevance and usefulness of CTS-SIM is partly an issue of how well it facilitates discussion and ongoing scientific interest. Establishing utility and interest is guided by the model's characteristics, points of reference that can focus discussion on a model's contribution, without restricting discussion to abstract arguments. As a guide to construction of the CTS-SIM environment, to facilitate transparency and to inspire critical discussion, I list below several stylized facts (patterns 'observed' to be broad and stable, see Chapter 3):

Stylized fact 1: *Directional opportunity exploitation*
In spite of the different views of opportunity exploitation, based on the differing pre-conditions for their 'existence', there is a general understanding in the entrepreneurship literature, that at some point (whether or not as a result of creation) opportunities must 'exist' for exploitation to take place. This fits with a directional, sequential model of the entrepreneurial process that begins with 'existing' opportunities (Fig. 2.2).

Stylized fact 2: *Externally driven environmental dynamics*
Turbulent environments are characterized by elements that interact among themselves and with the elements of organizations that operate within them. Change is also viewed as external to the organization and subjected to independent drivers that differ from those that drive internal change. This corroborates the seminal observations of Emery and Trist (1965),

that turbulence is a reflection of the degree of interconnectedness among the elements of the environment. Their Type IV environments possess dynamic properties arising not only from interaction among the organizational components but from the environment itself: the ‘ground is in motion’.

Stylized fact 3: *Diverse, transient opportunities*

The independent drivers of environmental change have encouraged their conceptualization as heterogeneous flows of fleeting opportunities. Although they may surface gradually in stable and mature markets, a broad ‘observed’ pattern put forth by the literature is that opportunities tend to be diverse and transient in highly dynamic markets. Studies ranging from the earlier works of Schumpeter (1942) to Kirzner (1997) characterize opportunities as able to generate initial incentives and payoffs that may fuel demand, but that are doomed by information diffusion and competition.

Stylized fact 4: *Continuous change*

A whole stream of entrepreneurship literature focussing on ‘newness and dynamism’, has built on Emery and Trist’s important characterization of turbulent exogenous environments. This stream views markets as processes of continuous change associated with uncertainty outside the control of decision-makers (e.g. D’Aveni, 1994; Teece et al, 1997; Eisenhardt and Martin, 2000). The ground is not only in motion, but in ceaseless motion.

There are two further characteristics that apply to CAS in general, to which CTS-type environments are ‘observed’ to belong:

Stylized fact 5: *Environmental uncertainty*

CAS researchers generally link the behaviours of complex, adaptive systems to which organizations belong with uncertainty, a mix of probability and behavioural unpredictability due to the rapid and changing interaction of a large number of environmental elements. (Exogenously driven uncertainty is closely linked to the uncertainty that decision-makers experience due to their own limitations, which is addressed in the next chapter).

Stylized fact 6: *Emergent environmental complexity*

Finally, there is some consensus, stemming from a wide range of multidisciplinary contributions since the beginning of research in the area of distributed artificial intelligence (e.g. Simon, 1962; Casti 1994; Anderson, 1999), that the interaction of many stochastic elements is associated with emergent sensitivity to small shocks that give rise to nonlinear path dependencies, sudden transitions and irregular patterns.

I therefore begin the modelling process with the aim of constructing an environment that can represent these characteristics: a large and diverse set of 'existing' opportunities, driven externally by continuous, stochastic flows of transience and change, which gives rise to nonlinear path dependencies due to their interdependencies. Following the Davis et al roadmap for developing theory using simulation, this section consists of five parts, beginning with the introduction of the RPX framework. Here I consider the key terms and their definitions and describe the variables of most relevance and significance.

The second part involves the quantification of the chosen variables for the exogenous environment i.e. establishing their ranges and values. The third part demonstrates the logical flow of the model, an opportunity to clarify the overall model process. The fourth addresses each of the underlying assumptions that have exposed themselves during model construction and the fifth addresses the steps taken to verify the model.

4.2.1 Construct and definitions

Opportunities and threats

At the root of CTS are opportunities. CTS-type environments are experienced by decision-makers as a superabundance of diverse, surprising and often apparently attractive opportunities. CTS-strategy is opportunity-based, as opposed to resource-based or position-based. Opportunities have been defined as: 1) 'a time, juncture or condition of things favourable to an end or purpose, or admitting of something being done or effected', 2) consisting of new ideas or beliefs about means or ends that, if acted upon, could yield gains and 3) 'situations with potential to alter the terms of exchange'.

Definition 1 (Oxford English Dictionary) associates opportunity with *a particular point in time and a place*[42] i.e. a location or position in space. Opportunities arise at a particular time and place either because they have not been *recognized* for some reason or because they have not been hitherto *discovered* or *created* due to a lack of either demand or supply or both. All three are possibilities commonly observed in practice.

Definition 2 (Sarasvathy et al, 2003) mirrors the role of opportunities in the exploitation process envisaged in the Intentions model, emphasizing their contingent nature i.e. the role of beliefs and perceptions and outcomes of value (positive or negative), 'if acted upon'. The range of issues constituting opportunities is simplified as far as possible into positive

[42] Oxford English Dictionary: Opportunity – a favourable time or set of circumstances for doing something.

(opportunity) and negative (threat) elements, based on the cognitive phenomenon of 'strategic issue categorization' (see Chapter 2).

Definition 3 (Kirzner, 1997) captures the context within which certain opportunity types (goods, services etc.) are closely associated with potential payoffs i.e. economic potentials. These situations are transient, highly so in the CTS context. They provide initial incentives for others who may validate them and fuel demand, but are doomed by information diffusion and competition.

I synthesise the above definitions by modelling opportunities here as potentials that deliver payoffs, positive or negative, arising at a particular time and place, either because they have not been *recognized* for some reason or because they have not been hitherto *discovered* or *created* due to a lack of either demand or supply or both – all three of which are possibilities commonly observed in practice.

RPX framework

The factors of time, place and contingency, and the desire to integrate the three views of opportunity 'existence', all place constraints on the modelling of entrepreneurial opportunities. They appear to support the modelling of opportunities on a spatial topology, but they challenge the more obvious notion of treating them as 'real' or 'pre-existent' i.e. doing so would evidently pass the recognition and discovery tests, but not the creation test.

A potential solution is to begin the modelling process by adopting a softer notion of the opportunity than the 'pre-existing' or 'real' opportunity, and to instead use the term *possible* or *realistic*, in order to pass the creation test and thereby better integrate these three views. A realistic opportunity or potential, therefore, should be understood as one that is possible to recognize, discover or create. Whether it is perceived as such, or acted upon, depends on the decision-making agent.

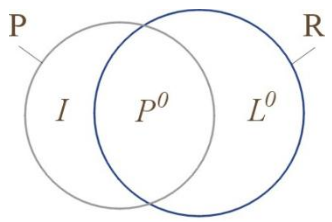
Whereas in practice an opportunity, or group of opportunities, may be 'observed' to have both positive and negative elements, I simplify here by weighing-up or aggregating these elements for decision-making purposes. In other words, in deciding which opportunities to seize, retain or abandon, decision-makers will weigh up their pros and cons and rank them in order of their perceived potential, by aggregating the positive and negative elements[43].

Using strategic issue categorization, and without restricting the ranges of values that either multiple positive and negative issues are likely to produce, I take the manager's action-based *preference ranking for opportunity seizure or abandonment*, P, and *realistic*

[43] Rankings may be based on discounted net present values, or whatever other method the manager finds suitable.

opportunity, R, as the initial concepts for opportunity pursuit in this model. R is a possible 'real' world, exogenously driven, and P the perceived world of the agent within the organization. R is understood to reflect all aspects of the exogenous environment – political, economic, social, technological etc. – that affect the organization, due to its own initiatives and those of its competitors.

These constructs are represented in Fig. 4.1, the 'initial state' of the RPX framework. Since decision-makers have often been found to be out-of-touch with environmental changes, perceptions and potentials are not expected to coincide completely (subsets P and R therefore not being fully superimposed). Indeterminacy due to imperfect perception skills may arise when elements of opportunities are perceived but *unrealistic* i.e. they are imagined, I (where $I \subset$ P). Further indeterminacy may arise when elements of opportunities are realistic but not perceived i.e. are initially latent, L^0 (where $L^0 \subset$ R).



P = opportunities perceived, R = 'realistic', I = 'imagined', P^0 = initial potential, L^0 = initial latent

Fig. 4.1. RPX: pre-action phase

The pre-action phase of the above mechanism is the foundation of CTS-SIM. At this early point in the opportunity exploitation process, R ∩ P represents potential for payoffs. It is only the initial source of potential, P^0. In the *action phase* that follows, further outcomes are likely to emerge. These are considered in the next chapter, where it becomes clear that R can be modelled in such a way that it represents the partly known, unknown and unknowable. In this chapter, focus is on the construction, observation and analysis of R and its drivers.

CTS-SIM environment

Recall that the hybrid constructivist position taken for this research does not consider objective knowledge to be impossible. So I started the modelling process with the 'existence' of opportunities (stylized fact 1), which calls for the capture of the external dynamics that drive them. I followed the conceptualization of CTS environments as diverse flows of ceaselessly changing, deeply interconnected, transient opportunities (stylized facts

2 - 4). My choices for drivers were arrived at in three stages (though not in the orderly, sequential fashion described here).

Step one entailed the isolation and development of alternative, ‘possible’ variables on a ‘clean sheet of paper’. This was an attempt to avoid potential limitations from focussing exclusively on the literature. Research limitations (biases, inaccuracies) can surface over time due to changes in the object of interest or developments in science. This seemed possible, especially given the short history of ABMS. Previous researchers may have considered other aspects of the environment, but been unable to capture or observe them in a useful way.

Another reason for taking this step was to avoid restrictions ahead of the modelling process. This can arise from pressure to conform to developing research streams and hence to miss an opportunity to creatively expand on them. A potential downside, in the event of choosing ‘new’ variables, is the introduction of personal biases, given the methodological framework adopted for this research.

Having isolated the candidate variables, I then explored the literature more thoroughly. Benefiting from the union of both personal and external sources meant 1) greater likelihood of a broader range of environmental aspects and 2) potentially interesting inconsistencies, and hence the possibility of further contribution.

Step three, choosing the most appropriate variables, was the culmination of an attempt to address all possibilities of this dyadic approach, first in terms of the goals and methods chosen and then in terms of building on previous research. This carried greater risk of introducing personal bias, but also greater potential benefit for the development of CTS. My approach here diverges from that taken during concurrent research by Davis et al (2007) who used the literature as the sole filter for choosing the variables in their simulation environment because previous research had shown them to be relevant.

Environmental variables: flows and change

Two variables are required to capture the ‘existence’ of opportunities: inception and cession[44]. I name the first *transience,* to capture the probability of opportunity cession and the second *frequency,* to capture the probability of opportunity inception. Opportunities tend to be incessant but short-lived in highly dynamic markets, so these variables represent the first step in an attempt to model stylized fact 3.

Change has been at the centre of research in highly dynamic environments, typically embedded in the textures or characterisations of most environments (stylized fact 4). I

[44] These are akin to birth and death in many other agent-based models.

considered three variables for the capture of essential elements of change. These have recently been noted to be able to impact the environment independently (Nadkarni and Narayanan, 2007). First, there is a need to capture the probability that change will take place. Second, there is a need to capture the probability that it is positive or negative. Third, there is a need to consider whether the change is large or small.

The model is able to capture all three. However, because the third variable (which allows the user to influence magnitude) had no observable effect on the simulation outcomes of interest in this research, I pay it no further attention. This leaves two essential variables for change, one to control its speed, the other its direction.

In sum, the CTS-SIM environment investigates four environmental dimensions:

1) Transience, *t*: probability of flow cession;
2) Frequency, *f*: flow persistence i.e. the probable speed of opportunity replacement;
3) Reversal, *r* (direction-based i.e. a positive changes are followed by negative ones and vice-versa);
4) Change-speed, *c* (time-based).

I use the acronym *tfrc* to refer to this group of variables.

Note that transience and frequency can be grouped together as *flows*, and speed and direction of change, *c* and *r*, as *change*. This is another, simpler and also useful way of understanding the behaviour of the environment based on its conceptualization as made up of opportunity flows and change. However, without transience, *t*, it would not be possible to bring about the end of an opportunity or model opportunity duration, necessary if stylized fact 3 is to be modelled. Without frequency, *f*, it would not be possible to generate opportunities essential to keep the model up and to facilitate ongoing choice (and hence to model stylized fact 12, next chapter). Without speed of change, *c*, it would not be possible to model stylized fact 4, a main focus of researchers in dynamic markets. Finally, a model ignoring reversal, *r*, would attribute no significant role to the direction of change, only positive payoffs characterizing opportunities throughout their lifecycles.

This is not to say that a more simply driven environment could not also be useful. However, deconstructing flows and change into four separate drivers from the bottom up offers a rich representation of the environment and is at least likely to inspire critical discussion, given the goal of guidance via reference points from earlier ‘observations’ of researchers.

So this is a straightforward start to the modelling process. It fits with the ‘Direction of the Entrepreneurial Process’ model by beginning the modelling effort with the ‘existence’ of a possible world containing opportunities. It is flexible enough for further development i.e. for population with decision-making agents, and the integration of the three views of entrepreneurial opportunity, in the next chapter. It is not a purely KISS approach given that there are four variables to drive the exogenous environment. This creates a large state-space. Unfortunately there is little reason to expect fewer variables to be as useful.

Environmental features

With the CTS-SIM environment now driven exogenously, as envisaged by stylized facts 1 - 4, what of stylized facts 5 and 6, environmental uncertainty and complexity? As shown in Chapter 2, the features of Schumpeterian environments at the top of most researchers' lists are 1) turbulence, 2) uncertainty, 3) dynamism, 4) munificence and 5) complexity. I consider the need to program these features into the simulation model.

Traditionally, *turbulence* has been difficult to measure, researchers content thus far to characterise it as 'dependence on the degree of interconnectedness among the elements' i.e. of the environment and the organization (Emery and Trist, 1965). Therefore, a large number of highly interdependent opportunities are prerequisites for the construction of a turbulent artificial environment. I model this by:

1) constructing a large number of cells (patches) on a grid to represent a 'field of interconnected opportunities' whose values affect one another;
2) programming the variables for opportunity flows and change, *tfrc*, such that they depend on one another in a logical way (Section 4.2.4).

Uncertainty is often used ambiguously to mean a reflection of the limits to decision makers' attention (agent uncertainty), when not taken to be the level of environmental indeterminism (model uncertainty). Treatment of agent uncertainty is an element of the system postponed to the next chapter. For CTS-SIM, as with most social systems, there are no known constants, so the aim is to strive to achieve a sufficient level of confidence without suppressing model uncertainty. Model uncertainty arises due to the interaction of variables that cannot be measured precisely i.e. contain irreducible variability, motto: 'we just do not know for sure' (stylized fact 5).

Modelling opportunities therefore requires that their 'existence' and values be partly dependent on chance, not just the result of fixing parameter settings. ABMS and NetLogo are predestined for the capture of such uncertainty. This enables the user to guide or shape behaviours, but not control them. It also means that many or longer simulations may be required for patterns to emerge, and calls for caution when interpreting simulation outcomes and making claims for the model.

Both *dynamism* and *munificence* are considered to be more amenable to measurement (Dess and Beard, 1984). Dynamism is a reflection of the absence of environmental pattern, measurable by rates of change and variation. As with the key features of complexity, unpacking the environment into *t, f, r* and *c,* on the scale described in the next section can incorporate rapid change and hide pattern at the lower level (stylized fact 6).

Munificence is a reflection of environmental capacity, measurable by rates of growth and profitability. Schumpeterian environments have been characterized as ‘a superabundance of diverse, surprising and often apparently attractive opportunities’. This does not exclude the possibility that they can be threatening too (Eisenhardt and Sull, 2001, p. 108): “Yahoo!'s rise can't be attributed to an attractive industry structure… it's characterized by intense rivalries, instant imitators, and customers who refuse to pay a cent… there are few barriers to entry.”

Hence, CTS environments possess both positive and negative elements that contribute to overall munificence. The modelled environment should therefore facilitate both growth and decay. How to capture both the attractive and unattractive attributes of such environments? As it turns out, the construction of an environment with sufficient opportunity potential, represented by R, enables both positive and negative aspects to emergent naturally as a result of the interdependence of the micro-level inputs.

Opportunities tend not only to be transient in highly dynamic markets but also diverse in nature. *Complexity* is characterized as ‘heterogeneous and dispersed in nature’ and as ‘emergent, nonlinear and uncertain’ (Dess and Beard, 1984; Holland, 1998; Sutcliffe and Huber, 1998). Hence, not only is there a need for a large number of interconnected opportunities, but for opportunities to be individually driven and heterogeneous across the ‘field’, each cell value shaped by its respective *tfrc* parameter setting.

Emergent attributes	*Interpretation*
Turbulence	degree of interconnectedness
Uncertainty	non-deterministic (due to irreducible variability)
Dynamism	change, absence of pattern associated with uncertainty
Munificence	capacity
Complexity	emergent, nonlinear, probabilistic, heterogeneous and dispersed

Table 4.1. CTS environmental attributes

Finally, before proceeding to the quantification of *t*, *f*, *r*, and *c*, there is a need to account for two further, pervasive features of CTS systems, *surprise* and *superabundance*. CTS-type environments were seminally characterised by Hayek as consisting of ‘a superabundance of diverse, surprising and often apparently attractive opportunities’. Because surprise is understood to be ‘a likely [human] response to something unexpected’, and superabundance relates to the alertness and the demand of the decision-maker, I take these to be system features rather than environmental features, and therefore postpone their capture to the next chapter.

4.2.2 Quantification

As indicated, ABMS borrows off proven techniques such as discrete-event modelling, with simulations being progressed as part of a synthesis of clock and event time. NetLogo executes commands asynchronously, each patch or agent executing its list of commands as fast as possible. Time is recorded as ‘time clicks’, or ticks, which accrue one by one, each time all commands have been executed.

Parameters

In NetLogo, *choosers*, *sliders* and *switches* are alternatives that enable users to set the value for a specified variable from a list of choices. These elements are accessible to all agents of a specified type and are used to enable changes in settings without having to rewrite the code. For CTS-SIM, each of the four variables, *tfrc*, was parameterized across its relevant range estimate, from low to high, with the help of a chooser and a drop-down menu, enabling one of seven settings for each variable (an example of which is shown in Fig. 4.2).

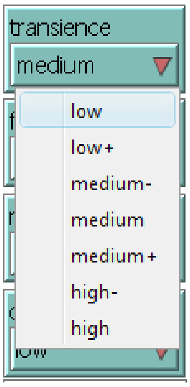


Fig. 4.2. *t* chooser

Opportunity flows and change

Programming each of the environmental dimensions, *tfrc*, was a two-step process:

1) a random number was drawn[45];
2) a probability was assigned (controllable via a parameter setting e.g. Fig. 4.2).

For example, a random number is generated from 0 to 9 (step 1). A high parameter setting (probability 80%) includes random numbers 0 to 7 and a low setting (probability 20%) includes only numbers 0 or 1. There are 7 settings for each variable (Fig. 4.2). These are abbreviated for presentation purposes as *l*, *l+*, *m-*, *m*, *m+*, *h-*, *h*.

The reason for this parameterization is pragmatic. With fewer settings it might be more difficult to observe and explain the effects of changes in dimensions. Fewer intervals can be too restrictive when searching for patterns or tensions among variables. On the other hand, more than seven settings might be impractical, as users are unlikely to distinguish between so many intervals. The settings are expected to affect the emergent dynamism and munificence. So, 'low' settings should not be taken as a low level of dynamism per se, but only as low relative to other settings.

Another question addressed at this point of model construction was 'What range of probabilities for each variable is most appropriate?' A high probability of opportunity cession, high transience, *t*, might be considered to be anything above 60%, a low probability anything below 30%. As a simplification, and in the absence any general evidence to the contrary, I used the strength of flexibility of ABMS by adopting a wide range of

[45] In NetLogo random numbers are 'pseudo-random', which is desirable for scientific modelling as they enable the replication of simulation runs if necessary (Wilenski, 2007). This is achieved by 'seeding' the random number generator (in NetLogo currently 'Mersenne Twister'), thereby generating the same sequence of random numbers.

probabilities, with limits of 80% and 20%. To control for these I also ran simulations with upper and lower limits of 95% and 5%.

Transience, t

The *t* chooser permits control of the *probability* that an opportunity will cease to generate a value for R. The moment the value of an opportunity drops below that at the previous tick, there is a chance it will cease to generate values altogether. The probability of this occurring depends therefore not only on *t*, but also on there being a precipitant turn for the worse. This is affected by the variable *r* (see below).

A *low t* setting, 20%, means that an opportunity will cease to generate a value for R every fifth tick on average. In other words the duration of the opportunity will be *roughly* 5 ticks, the incidence of *t*, as with the other variables, being uncertain. A *medium t* setting, at 50%, means an opportunity will cease to generate a value every second tick or so, and a *high t* setting, at 80%, almost every tick.

Frequency, f

The *f* chooser permits control of the probability that an opportunity will be generated where transience has ended an opportunity or where none previously 'existed' i.e. where the value of an opportunity patch is zero (see topology below). The procedure for influencing new value generation through frequency, *f*, is the same as that for influencing cession through transience, *t*.

Change, c and r

Environmental change is controllable via the two variable settings for speed[46], *c*, and reversal, *r*. The procedures mirror those above.

The environment is driven by highly interdependent elements i.e. there are no independent variables. I assume (see next section) that opportunities do not simply cease without reason from one tick to the next, but are precipitated by either changelessness or a downturn. So the cessation of opportunities depends on their being triggered (*t* depends on *r*). Also the direction of change is dependent on the speed of change (*r* depends on *c*). The relationships between all of the other variables are interactive:

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[46] Note that the random element of change builds in discontinuity. Bourgeois and Eisenhardt (1988) observe that in high-velocity environments, changes are rapid and discontinuous.

1) Transience, *t*:
   - depends directly on reversal, *r*;
   - depends indirectly on frequency, *f* i.e. on the 'existence' of an opportunity;
   - depends indirectly on the speed of change, *c* (since reversal, *r*, depends directly on *c*);
2) Frequency, *f*:
   - depends partly but directly on transience, *t* i.e. it depends on transience having ended an opportunity as well as patches where none previously 'existed';
   - depends partly but directly on change, *c* and *r*, since *t* depends on *c* and *r*;
3) Reversal, *r*:
   - depends directly on the speed of change, *c*;
   - depends indirectly on the existence of an opportunity i.e. on both *t* and *f*;
4) Speed of change, *c*:
   - depends directly on the 'existence' of opportunities and hence on frequency, *f*, and partially and indirectly on transience, *t*.

Note also that even a low setting for frequency, *f*, ensures a flow of opportunities on the grid. This keeps the environment up. So *f* impacts the levels of dynamism and munificence, along with the other drivers, *trc*.

The opportunity field

Opportunities are captured and displayed in CTS-SIM on a spatial topology, a two-dimensional grid, abundant with R. They are generated in cells. There is no need to firmly partition single and groups of opportunities. The latter merely possess 'highly similar, closely-related features and obviate the need to distinguish between them'. Such a group can be understood to find itself on one-and-the-same cell. As indicated, opportunities may have positive and negative elements. So their values at a particular point in time may be positive, zero or negative. For CTS-SIM:

1) *Single* (or groups) opportunities are situated on cells represented by patch agents on the grid.
2) *Aggregate* opportunities are the total of all the patches.
3) *Cumulative* opportunities refer to the total of all the patches *accumulated over time*.

Figure 4.3 shows values for R on the CTS-SIM grid at a point in time, stopped during a simulation. Each patch generates a sequence of values for R at each tick. A zero indicates either the presence of an opportunity with value zero, or the absence of an opportunity. The former can be caused by changes in *c* and *r*, the latter by transience, *t*, in the absence of inception or substitution, *f*. Frequency, *f*, controls the probability of a new opportunity being generated. Each patch therefore generates a probable sequence of opportunities during a simulation, each with a unique, partially deterministic, path and duration.

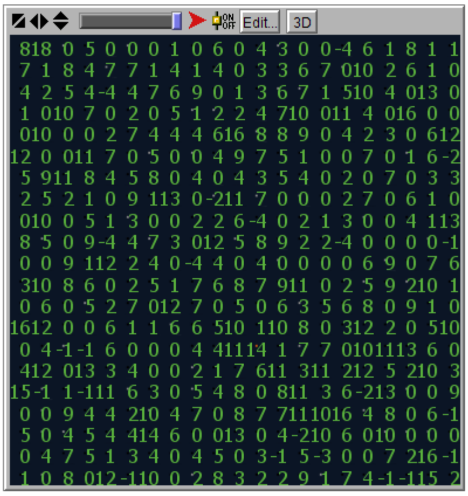

Fig. 4.3. Opportunity field showing R values at a point in time

The size of the opportunity field can be altered easily by using the three sets of black arrows in the upper left corner of the 2D grid above. Field size is important only to assure that there is opportunity *superabundance*, which is accounted for in the next chapter. The 20 x 20 field shown in Fig. 4.3 proved sufficient for the purposes of this research[47]. The distance between cells, often a key feature of cellular automata models, plays no role in the version of CTS-SIM developed in this research[48].

In the next chapter, the extended model requires a number of other values of interest to be processed on each cell. With so many values changing each tick on so many cells, such computational demands are best addressed with the use of computers.

4.2.3 Main assumptions

Specifying the main underlying assumptions is an issue both of scope (model specification) and of simplification (balance between ontological adequacy and parsimony). An advantage of ABMS over traditional methods of strategic management research is its

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[47] During the development of the model larger fields were tested which slowed execution without any apparent gain.

[48] Models in which spatial interactions are not considered necessary are commonly referred to as 'soup models'.

ability to expose important assumptions made during model construction that are otherwise easily overlooked in text.

1) Relative values assumption

In practice, one might expect a certain opportunity to be dependent on others, but not expect this of all opportunities. So, across the entire opportunity field, the degree of interdependence could differ. A cell would therefore have a certain R value in the presence of other related opportunities, but a different value in their absence.

Although there may be alternative solutions[49], a simplification is to treat *all R values on the CTS-SIM grid as relative i.e. no value at a point in time is understood in isolation*. This is possible because some R values can be expected to change at every tick on a large grid (stylized fact 4), and change unpredictably (stylized fact 5). This follows Emery and Trist's Type IV conceptualization of the environment as a richly connected turbulent field.

2) Transience assumption

An advantage of ABMS for this research is that bold assumptions about the range of transience, *t*, across the opportunity field, are avoidable. However, what triggers the end of an opportunity? I assume that *an opportunity does not simply cease without reason from one tick to the next, but instead must be precipitated by either changelessness or a downturn*. Although such precipitators can signal cession, agents may completely overlook them (see next chapter). Furthermore, the requirement that cession is first triggered 'breathes life' into opportunities i.e. prevents any possibility of transience acting immediately on newborn opportunities.

3) Flow assumption

For transience, *t*, and reversal, *r*, there is a need to establish *flow*, the direction of change at the previous tick. There are three possibilities: either there is no previous change in R, an increase (*posflow*), or a decrease (*negflow*). Flow assumptions are pivotal. Two alternatives were considered and tested:

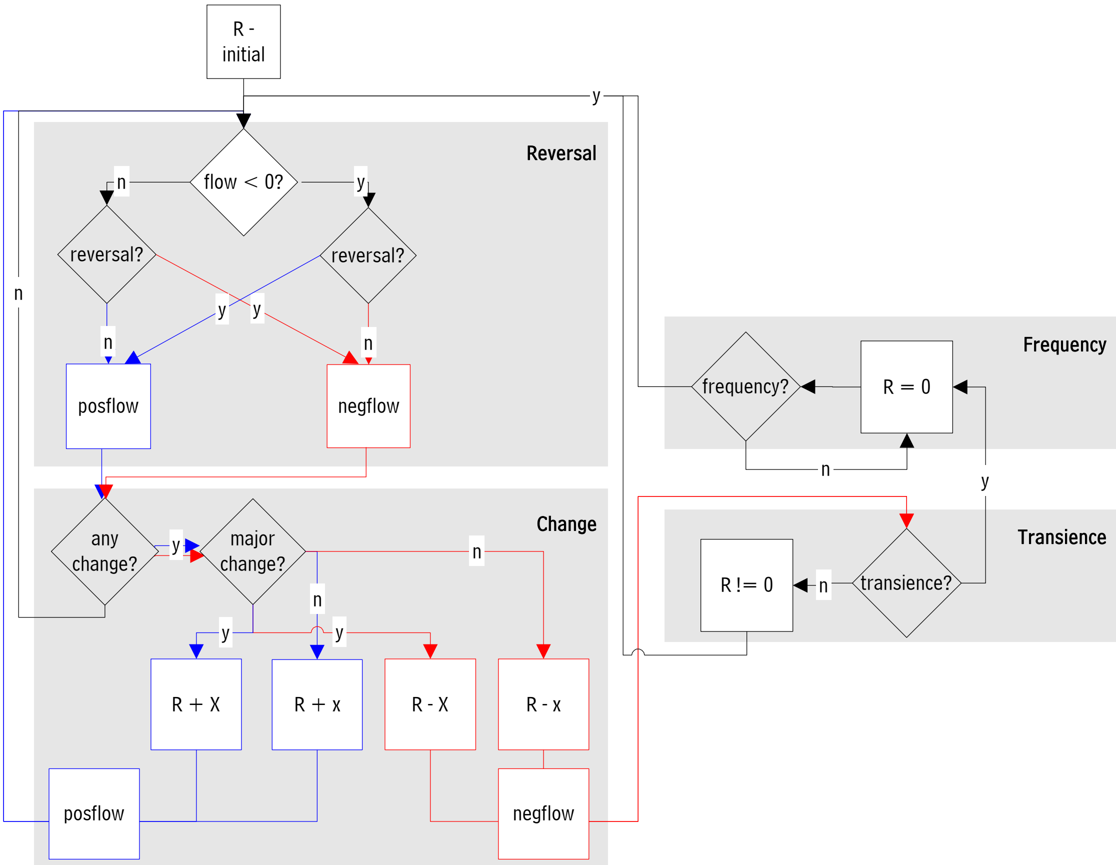
1) Negflow is defined as *no increase in R* (i.e. $R^{t+1} \leq R^{t}$).
2) Negflow is defined as a *decrease in R* (i.e. $R^{t+1} < R^{t}$).

[49] A way of addressing differential interdependencies among opportunities might be on the basis of their location on a multi-dimensional grid: the shorter the distance between them, for example, the higher the degree of interdependence.

Transience, *t*, will therefore be triggered sooner under assumption 1, when changelessness suffices, than under assumption 2, when a downturn is necessary. In other words, assumption 2 is more positively biased than assumption 1. I test the sensitivity of the model to both assumptions (see Experiment 2.2 in this chapter, and Experiment 5.4 in the next chapter), assuming flow assumption 2 unless otherwise stated.

4.2.4 Processes

It is useful to consider the logical flow of R, before progressing to the simulation stage. The simplified flowchart below (Fig. 4.4) depicts the programmed environment.



R = realistic opportunity value ! = not equal to X = major effect x = minor effect

Fig. 4.4. CTS-SIM environment

The grey shaded areas depict the algorithms for each variable. At the beginning of each tick the system calculates the *flow* value i.e. the difference between the current value for R and the value at the previous tick. The algorithm for reversal, *r*, has an influence on whether flow direction changes from positive to negative or vice-versa, depending on the chooser setting.

The algorithm for change has an influence on whether the reversal from the previous algorithm is adopted or not, depending on the settings for speed of change, *c.* A negative change is a signal for potential opportunity cession (flow assumption 2). The algorithm for transience, *t*, has an influence on whether R is reset to zero or not, depending again on the setting. An R-value of zero indicates an opportunity with zero value or the absence of an opportunity. Flow renewal, and hence munificence and abundance, is also shaped by the algorithm for frequency, *f*[50].

Fig. 4.4 not only underscores the interdependence of the micro-level variables, *tfrc*, but also the micro-macro environmental feedbacks. For example, whereas the incidence of transience is shaped by the *t*-setting, the extent of transience (how many opportunities disappear at a point in time) is obviously influenced by aggregate R, the macro-status of the environment. The same applies to the other variables, *f, r* and *c*.

4.2.5 Verification

Verification refers to operational efficacy i.e. ensures that the model contains no errors, oversights or bugs (North and Macal, 2007).

Monitoring and debugging

A feature of NetLogo software is that it can be used to issue the first 'automated salvo' in the CTS-SIM battery of verification tests. Syntax checking, a command centre to test individual commands, a runtime error-message reporter and a facility to slow down or stop execution are NetLogo tools that simplify the process of error detection.

Besides these built-in facilities, consistent use was made of the agent monitor and commander tools, which permitted active tracking of changes in the specifications belonging to a chosen agent. Here, when necessary, the behaviour of agents (coordinates, colours, values etc.) could be tracked both between and during simulation runs by stopping it

[50] The flowchart shows change in both speed and magnitude. As indicated, the variable for magnitude was discarded for the purposes of this research.

for inspection. Rigorous checks for functionality were also enabled using monitors that display changes in values several times per second. At times, slowing the simulation down was sufficient to track behaviour on the grid, with colours and labels signalling changes. These features proved useful not only for verification purposes, but also for statistical analysis, as gauges and variables were used to export data to Excel 2007.

Coding of the model and verification were undertaken concurrently and proved, as expected, to be a time-consuming undertaking during the construction phase. The outcome is a model that works as intended, and that can 'breathe life' into the RPX construct.

Sensitivity testing

The goal of sensitivity testing is a common one, as Carley notes (1996, p. 12), "to establish that the simplifications made in designing the model do not seriously detract from its credibility and the likelihood that it will provide important insights." I conduct sensitivity tests in this section and in the sections that describe the experiments, to help understand both the sensitivity of the environment to its drivers and the sensitivity of outcomes to the main underlying assumptions.

The simulation runs below serve as additional verification that the environment operates as intended i.e. they show that the dimensions of the exogenous environment follow the fundamental rules for *tfrc* as described. Rivkin (2000), for example, ran his simulation of strategic imitation at various values of strategic complexity to confirm that model specification was complete and his model programmed correctly.

The graphs that follow are a dynamic representation of R trajectories. They show R values (*y*-axis) as they unfold over time, t (*x*-axis) for a randomly selected opportunity sequence (i.e. on cell 13).

The graphs are labelled *variables: settings*. For example *tfrc: hhhh* shows outcomes when the parameter settings for transience, frequency, reversal and change are all *high*.

1) Verification test for 'fleeting time frames'

The *t* chooser permits control of the probability that an opportunity will cease to generate a value for R. A higher *t* setting should increase the disruption to opportunity lifecycles and therefore a sequence of opportunities should present with more *peaks* than at lower *t* settings, at least over longer runs. As expected, the model produces longer opportunity lifecycles when the *t* setting is low than when it is high (Fig. 4.5). There are fewer peaks in the top row when transience, *t* = low, than the bottom row, when *t* = high. This is confirmed regardless of *frc* levels.

Note that the graphs show behaviours at extreme settings for *t*. Behaviours at interim settings (*l*+, *m*-, *m* etc.) are reported in Section 4.3.

Patch 13

Transience, *t*

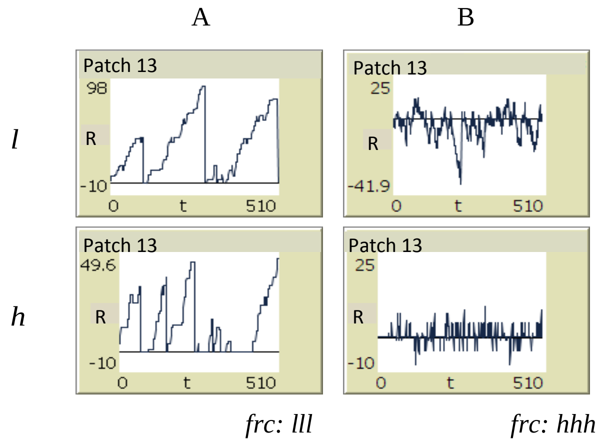


Fig. 4.5. Effect of *t* on R for a single opportunity

(Graphs show low *frc* levels [column A] and *high* levels [column B] for randomly chosen patch 13)

2) Verification test for incessant, path-dependent opportunity flows and change

The *f* chooser permits control of the probability that an opportunity will be generated where none previously 'existed'. A higher *f* setting should increase the incidence of new opportunities in a sequence and show shorter *plateaus* at zero-value. Fig. 4.6 confirms this behaviour i.e. plateaus are longer at *t low* (top row) than *t high* (bottom row). This is easier to see at *high trc* levels (column B).

Patch 13

Frequency, *f*

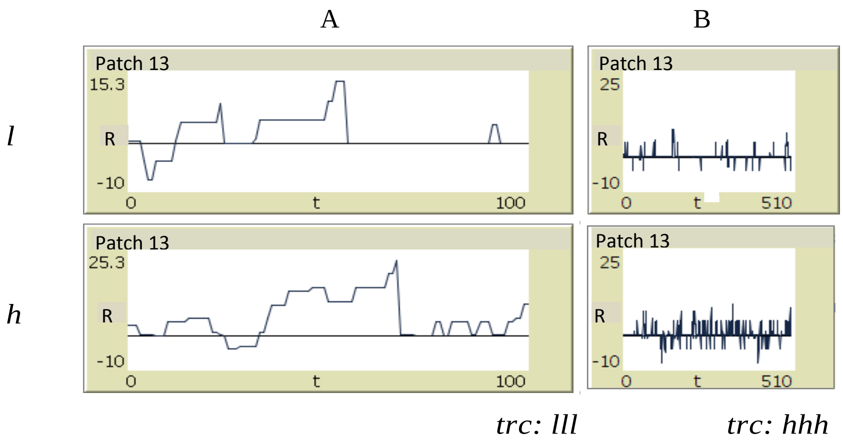


Fig. 4.6. Effect of *f* on R for a single opportunity

(Graphs show low *trc* levels [column A] and *high* levels [column B] for randomly chosen patch 13)

Environmental change is controlled via the two variable settings for change, *r* and *c*. A higher *r* setting should have a *dampening* effect on the R trajectory, preventing the development of an opportunity in a particular direction, compressing it downward toward value zero (*y*-axis). Again, as expected, Fig. 4.7 follows the intended fundamental behaviour: R trajectories are more expansive at *low r* (top row) than *high r* (bottom row) – note the *y*-axis values.

Patch 13

Reversal, *r*

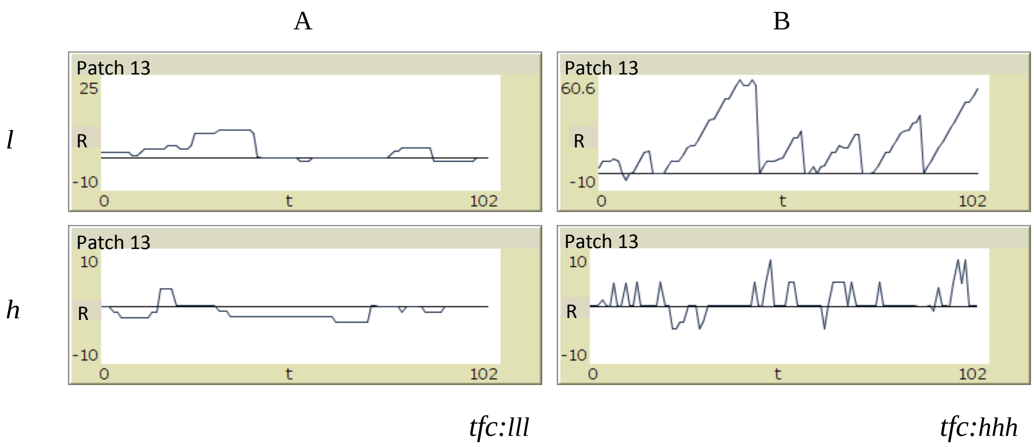


Fig. 4.7. Effect of *r* on R for a single opportunity

(Graphs show low *tfc* levels [column A] and *high* levels [column B] for randomly chosen patch 13)

The *c* chooser permits control of the probability that changes in R will take place at all. A higher *c* setting should accelerate the occurrence of change, compressing the R trajectory along the *x*-axis. Fig. 4.8 follows the expected fundamental behaviour, more change taking place in the same period of time. Furthermore, trajectories are continuous and path-dependent, current values based on changes to past values. However, although history matters, trajectories are unique i.e. future values are only loosely linked to the past.

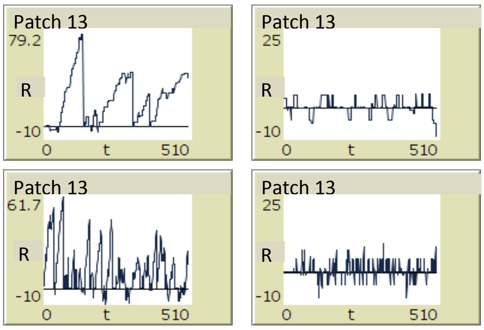
Patch 13

Change-speed, *c*

A B

l

h



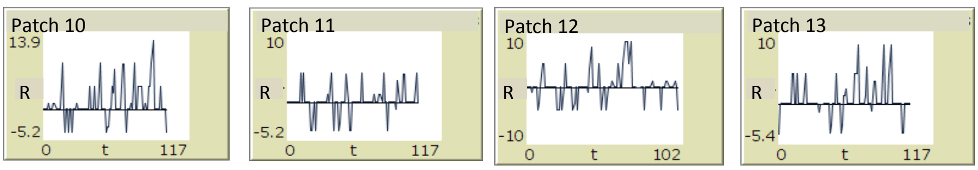
tfr:lll *tfr:hhh*

Fig. 4.8. Effect of *c* on R for a single opportunity
(Graphs show low *tfr* levels [column A] and *high* levels [column B] for randomly chosen patch 13)

3) Confirmation of the diversity of opportunity flows

Finally, heterogeneity is assured for all R trajectories, not only for observations of R on the same cell over repeated runs, but for all values of R across the field, as shown in the example below (patches 10 - 13):

Patches 10 – 13



tfrc: *hhhh* *hhhh* *hhhh* *hhhh*

Fig. 4.9. Heterogeneity of opportunities across patches
(each patch has the same *tfrc* settings)

In sum, these test simulations complement the monitoring and debugging efforts conducted during construction of the exogenous CTS-SIM environment. The presence of peaks, plateaus, dampening effects and unique R trajectories demonstrate how a diverse set of continually changing values on a large grid might be used to represent uncertain and short-lived, but identifiable and promising opportunities. Davis et al (2007, p. 492): "If the simulation confirms the propositions, then the theoretical logic and its computational representation are likely to be correct." This section provides some initial evidence that R, guided by *tfrc*, could be a useful and interesting representation of CTS environments.

4.3 Experimentation

The general aim of the experiments that follow is *to examine the causal mechanisms between the drivers of the modelled 'highly dynamic' environments and their emergent behaviour*. I describe these experiments by focusing on how the drivers, *tfrc*, influence the emergent dynamism and munificence of R.

4.3.1 Experiment #1: *Investigating the combined effects of flows and change on dynamism and munificence*

Aim is to test how an increase in the levels of flow and change (increase in *tfrc* in unison) impacts environmental dynamism in terms of variance, and how it impacts munificence in terms of capacity. Any observable impact would point to a causal mechanism enabling the user to influence these aggregate environmental attributes, by changing the settings for *tfrc*. This is a first step in the direction of the core research aim, to contribute to a better understanding of opportunity-transitioning in highly dynamic environments.

Below are results of simulations that show R in terms of dynamism and munificence at the individual and aggregate levels, and over time, varying the level of *tfrc*. This has not been done in this manner before.

Graphs show R at various *tfrc* levels at the individual level (on a single, random cell), aggregate level (total value on the grid) and accumulated over time. It is useful to examine the behaviour of R on a single patch because the exogenous environment can be expected to impact the perceptions of the individual decision-making agents, P, and therefore their performance. It is also useful to examine the behaviour of R on the entire field, over time, because the exogenous environment can be expected to impact the perceptions and performance of the organization as a whole (see next chapter).

Settings[51]

Experiment #1		Variables				Sample		Reporter
		t	*f*	*r*	*c*	*runs*	*ticks*	
1.1	1	*l*	*l*	*l*	*l*			R (random cell)
	2	*m*	*m*	*m*	*m*			
	3	*h*	*h*	*h*	*h*			
1.2	4	*l*	*l*	*l*	*l*			R (aggregate)
	5	*m*	*m*	*m*	*m*	*4*	*100*	
	6	*h*	*h*	*h*	*h*			
1.3	7	*l*	*l*	*l*	*l*			R (cumulative)
	8	*m*	*m*	*m*	*m*			
	9	*h*	*h*	*h*	*h*			

Table 4.2. Settings for Experiment #1

Outcomes, observations

<u>#1.1. R: *single cell*</u>

The top row in Fig. 4.10 shows unique, nonlinear, probabilistic R trajectories for all four runs on a random patch at different *tfrc* levels.

Dynamism in terms of variation in the R trajectories appears to increase at higher *tfrc* levels. These trajectories show a high level of munificence for the most part i.e. good capacity for growth, though this is not assured throughout the simulation as expected of a complex system (top row, column B).

The second and third rows in Fig. 4.10 also appear to show a break down or draining away of munificence with more peaks, plateaus and compression of R on both axes (this is clearer at the aggregate level).

[51] Simulation results for the purposes of these experiments were no different at range settings 80/20 from those at 95/5 (see Section 4.2.2), so only the former are shown here.

Patch 13

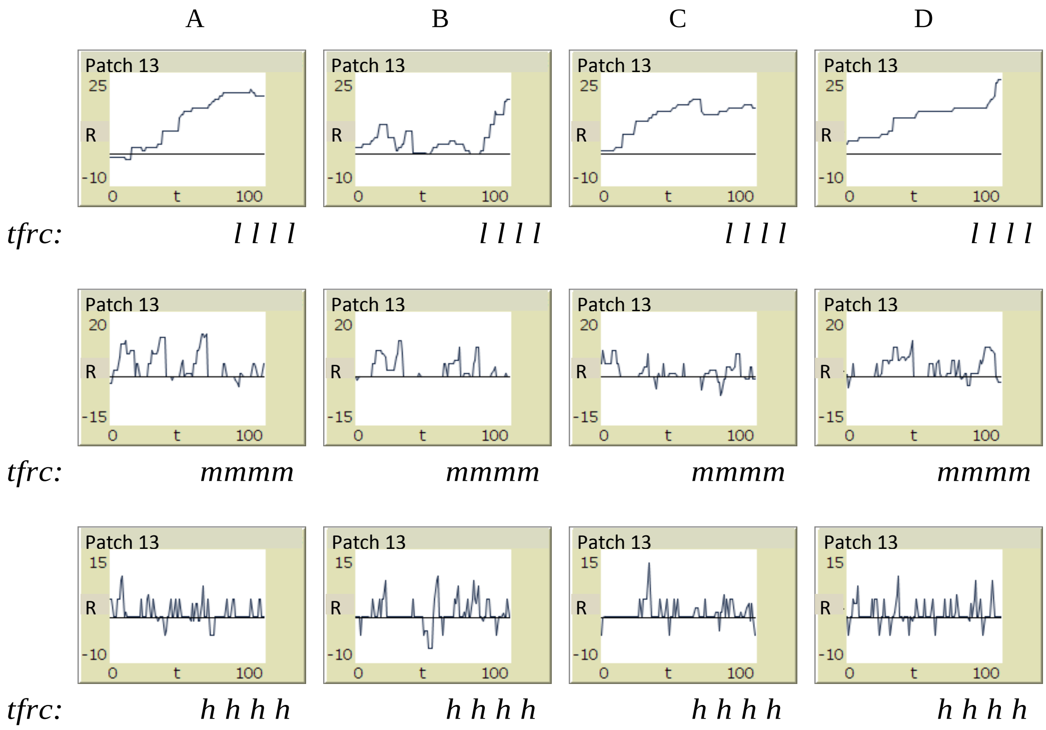


Fig. 4.10. Path dependence of R for a single opportunity

(Graphs show 4 different paths for R with *tfrc* at *low*, *medium* and *high* levels)

<u>#1.2. *Aggregate* R</u>

The R trajectories shown in Fig. 4.11 are less obscure. It is also easier to observe at this level how environmental dynamism increases in terms of the loss or absence of pattern in the R trajectories at increased levels of *tfrc*. Environmental munificence also drains away observably (note *y*-axes).

Aggregate R

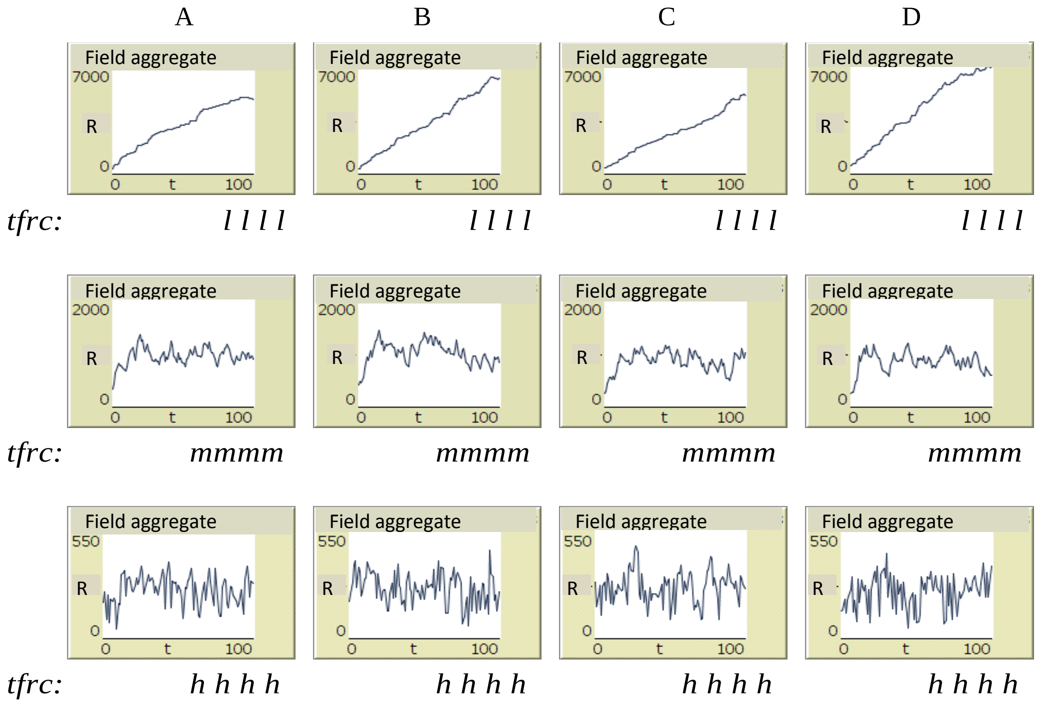


Fig. 4.11. Path dependence of R for the entire field

(Graphs show 4 different paths for R with *tfrc* at *low, medium* and *high* levels)

#1.3. *Cumulative* R

In Fig. 4.12 the effects of increased *tfrc* on R over time, though hidden in the case of dynamism, are most obvious in the case of munificence (again note the *y*-axes),.

Cumulative R

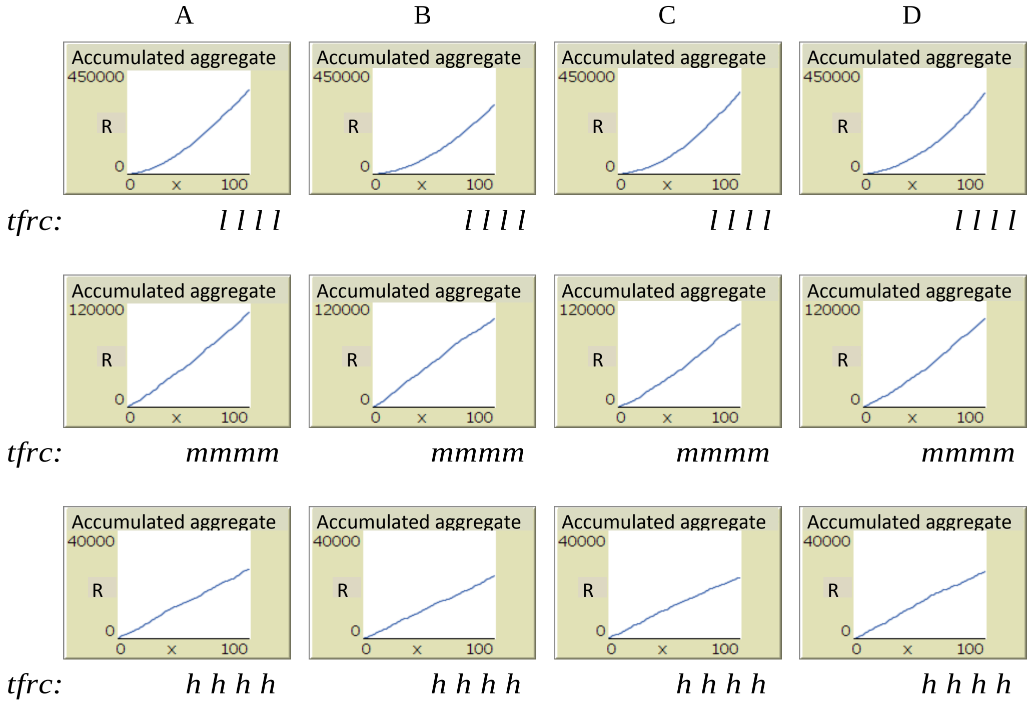


Fig. 4.12. Path dependence of R for the entire field over time
(Graphs show 4 different paths for R with *tfrc* at *low, medium* and *high* levels)

Facit: The above simulations show the emergence of dynamism in terms of variance, munificence in terms of capacity, and complexity in terms of emergent, nonlinear, probabilistic, heterogeneous and dispersed behaviour. At the lower level (the single opportunity sequence), outcomes are less visible, patterns only emerging at the aggregate and cumulative levels. At these levels a general increase in the levels of *tfrc* reveal general causal effects on dynamism (positive) and munificence (negative). Changing the settings for all four drivers, *tfrc*, in combination can affect these aggregate behaviours. The individual effects of each of the drivers on dynamism and munificence are shown in the next experiment (Table 4.5).

4.3.2 Experiment #2:
Investigating the individual effects of flows and change on munificence and dynamism

I perform the same tests as before, but change *t, f, r* and *c* individually. Unpacking the four drivers is an interesting way of investigating their individual causal roles.

Below are results of simulations that report R in terms of dynamism and munificence at the individual and aggregate levels, and over time, varying either *t*, *f*, *r*, or *c*.

Because a tension between *t* and *r* is revealed, the above simulations are followed by sensitivity tests to the flow assumption (see Section 4.2.3).

Settings

Experiment #2		Variables		Sample		Reporter
		tfrc	*tfrc (control)*	*runs*	*ticks*	
2.1	1	*lhhh*				
	2	*hlhh*				R (random cell)
	3	*hhlh*				
	4	*hhhl*				
	5	*lhhh*				
	6	*hlhh*	*hhhh*	*1*	*100*	R (aggregate)
	7	*hhlh*				
	8	*hhhl*				
	9	*lhhh*				
	10	*hlhh*				R (cumulative)
	11	*hhlh*				
	12	*hhhl*				

Table 4.3. Settings for Experiment #2.1

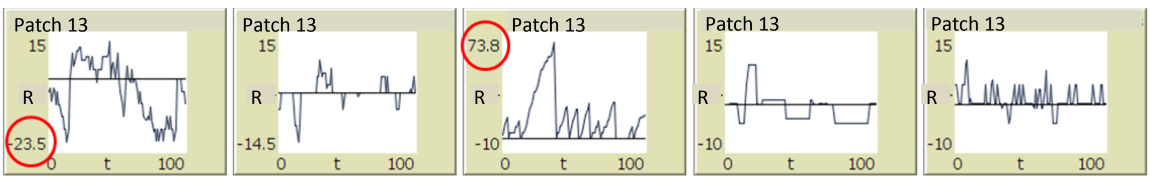
Outcomes, observations

#2.1. R: *single cell*

Fig. 4.13 shows the effect on R of changes in each of *t*, *f*, *r* and *c* at the individual opportunity level. Comparing Fig. 4.13*a* with Fig. 4.13*e* shows the effect on R of an increase in *t*; comparing Figs. 4.13*b* with *e* shows the effect of an increase in *f* on R; comparing Figs. 4.13*c* and *e* shows the effect of an increase in *r*, and comparing Figs. 4.13*d* and *e* shows the effect of an increase in *c*. (These behaviours should be familiar from the verification tests conducted in Section 4.2.5.)

Patch 13

low *transience* low *frequency* low *reversal* low *change-speed*



tfrc: *l h h h* *(a)* *h l h h* *(b)* *h h l h* *(c)* *h h h l* *(d)* *h h h h* *(e)*

Fig. 4.13. Effects of *t*, *f*, *r* and *c* on R for a single opportunity

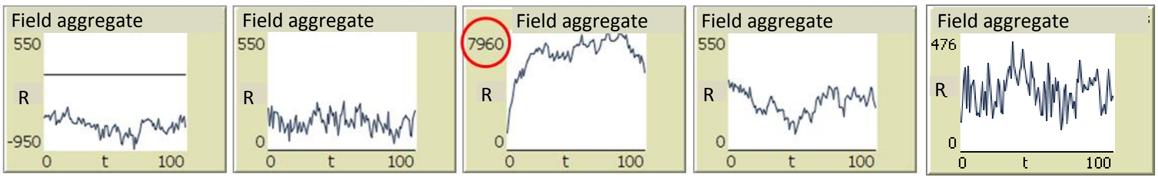
(Compare each graph with graph *e* on the right for the effect of *t*, *f*, *r* and *c* on R respectively)

#2.2. *Aggregate* R

Fig. 4.14 below shows the effects of changes in each of the above variables on R at the aggregate level, again comparing Fig. 4.14*a* with *e*, Fig. 4.14*b* with *e* and so on. Note the potentially positive effect of increased transience on R, and the negative effect of increased reversal on R.

Field Aggregate

low *transience* low *frequency* low *reversal* low *change-speed*



tfrc: *l h h h* *h l h h* *h h l h* *h h h l* *h h h h*

(a) *(b)* *(c)* *(d)* *(e)*

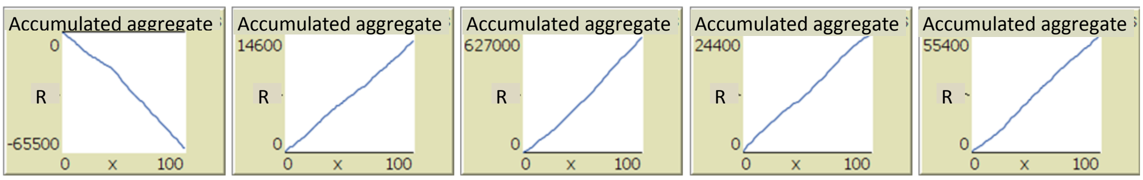
Fig. 4.14. Effects of *t, f, r,* and *c* on R for the entire field
(Compare each graph with graph *e* respectively)

#2.3. *Cumulative* R

Fig. 4.15 below shows the effects of *t, f, r* and *c* on R at the cumulative level, over time, again comparing Fig. 4.15*a* with *e*, Fig. 4.15*b* with *e* and so on. Again, note the differing effects of transience and reversal on R (i.e. the positive effect of increased transience on R, and the negative effect of increased reversal on R).

Cumulative

low *transience* low *frequency* low *reversal* low *change-speed*



tfrc: *l h h h* *h l h h* *h h l h* *h h h l* *h h h h*

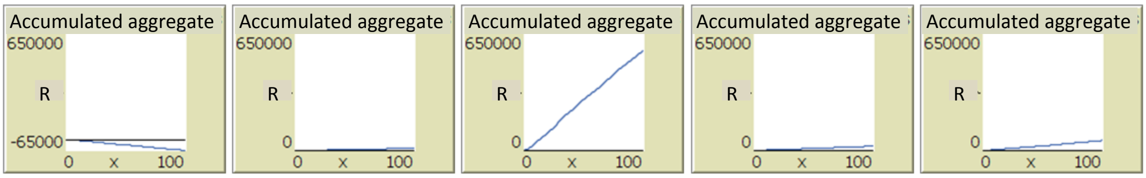
(a) *(b)* *(c)* *(d)* *(e)*

Fig. 4.15. Effects of *t, f, r,* and *c* on accumulated R for the entire field over time
(Compare each graph with graph *e* respectively)

Two interesting outcomes emerge from the aggregate and cumulative graphs (Figs. 4.14 and 4.15): 1) transience at high levels of flow and change has a positive effect on munificence, and 2) reversal has a negative effect (note the value on the *y*-axis).

Neither outcome is intuitive. One might expect an increase in transience (hence opportunities of shorter duration) to decrease environmental munificence, *ceteris paribus*. Conversely, a decrease in transience (hence an increase in the duration of opportunities) should increase munificence. The above simulations point in the opposite direction. Moreover, one would not necessarily expect low reversal to increase munificence *ceteris paribus*, or high reversal to decrease it, yet they clearly do. These effects are more obvious when the *y*-axes are fixed (Fig. 4.16 below):

Cumulative (fixed y-axes)



tfrc: *l h h h* *h l h h* *h h l h* *h h h l* *h h h h*

(a) *(b)* *(c)* *(d)* *(e)*

Fig. 4.16. Effects of *t*, *f*, *r* and *c* on accumulated R with *y*-axes fixed

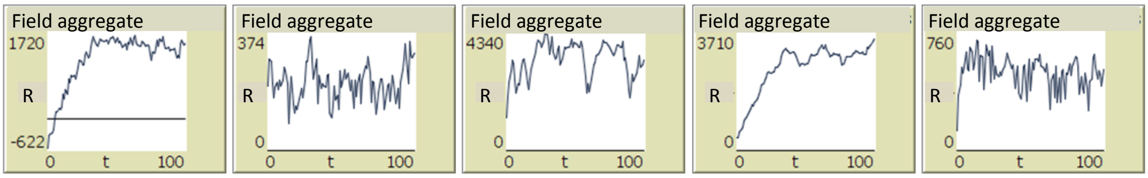
I pursue the outcomes for transience briefly below, and explore those for reversal in connection with Experiment 3.

<u>#2.4. *Sensitivity to transience and flow assumptions*</u>

The positive effect of increased transience on R might be due to its positive effect on frequency i.e. the higher *t* then the greater the effect of *f*, since *f* acts on opportunities with value zero. If *t* were zero, for example, then there could be no *f*, no creation without destruction. However, there is a need to test the sensitivity of the above outcomes to the flow assumption. In the above experiment, a downturn was necessary to trigger transience (assumption 2). In the experiment below, transience is already triggered when there is no change in R (assumption 1).

The effect on the exogenous CTS-SIM environment of a change in the flow assumption is dramatic, reversing it (compare Fig. 4.14*a* with Fig. 4.17*a*).

Field Aggregate



tfrc: *l h h h* *h l h h* *h h l h* *h h h l* *h h h h*

(a) *(b)* *(c)* *(d)* *(e)*

Fig. 4.17. Effects of *tfrc* on R for the entire field (*flow assumption 1*)

Thus, whereas for flow assumption 2, increased transience has a positive effect on munificence, reversal a negative effect, under flow assumption 1 both transience and reversal have negative effects on munificence (note the *y*-axes).

Before abandoning flow assumption 1 due to its lack of intuitive appeal (a downturn being taken as a likely precursor to opportunity cession), I compare the effect of transience on R at both high and low levels of *frc* for both assumptions:

Settings

Experiment #2 (continued)	Variables		Sample		Flow assumption	Reporter
	t	*frc*	*runs*	*ticks*		
1	*l, m-, m+, h*	*l l l*	*1*	*100*	*negflow:* $R^{t+1} \leq R^{t}$ (i.e. alternative 1)	R (aggregate)
2	*l, m-, m+, h*	*m m m*				
3	*l, m-, m+, h*	*h h h*				
4	*l, m-, m+, h*	*l l l*	*1*	*100*	*negflow:* $R^{t+1} < R^{t}$ (i.e. alternative 2)	R (aggregate)
5	*l, m-, m+, h*	*m m m*				
6	*l, m-, m+, h*	*h h h*				

Table 4.4. Settings for Experiment #2.2 (cont.)

Each row of graphs in Fig. 4.18 below shows the incremental effects of increasing transience on R. Column A shows these effects at low levels of *frc*, column B at medium levels of *frc* and column C at high levels of *frc*.

Based on flow assumption 1, although transience has an incrementally *negative* effect on R, this is only at high levels of dynamism (column C). At lower levels (column A), in other words in less dynamic environments[52], transience has an incrementally *positive* effect on R:

[52] I refer to environments with high *tfrc* settings as highly dynamic (as opposed to chaotic, for example), for convenience.

Field aggregate

Transience, *t*

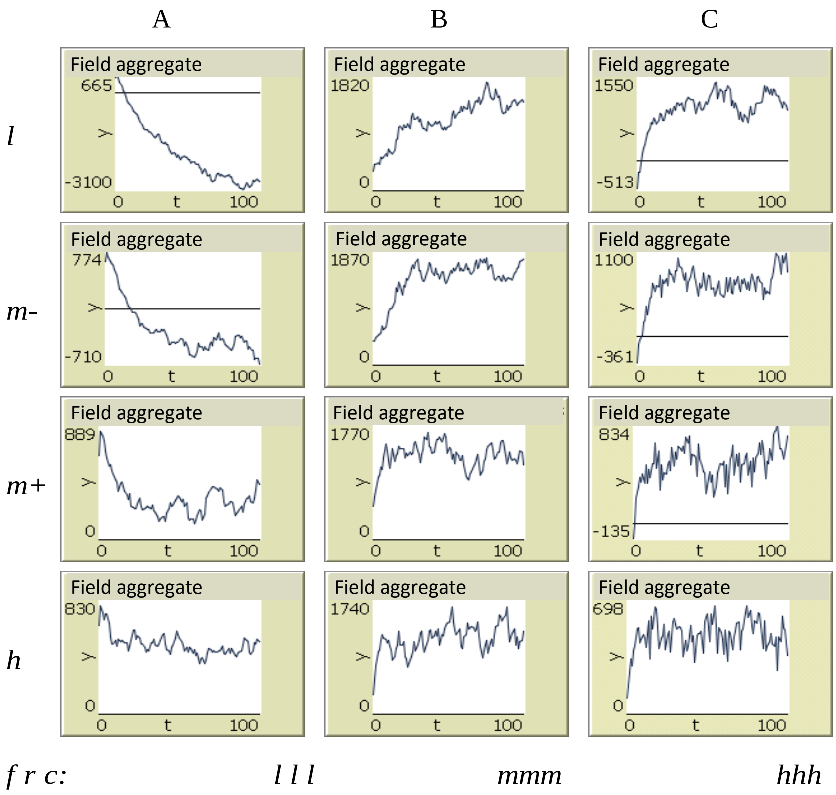


Fig. 4.18. Effects of increasing *t* on R for entire field (*flow assumption 1)*

(Graphs show effects at different levels of *frc*)

Based on flow assumption 2, the incremental effects of transience on R are reversed. The effect of transience on R is negative at low levels and positive at high levels (Fig. 4.19, columns A and C). The effect of transience on R in the CTS-SIM exogenous environment is therefore contingent on the other levels of flow and change.

Note the effects of increases in transience, *t*, on R at medium levels of *frc*. Interestingly, the effect on R of even a large increase in transience may be barely observable.

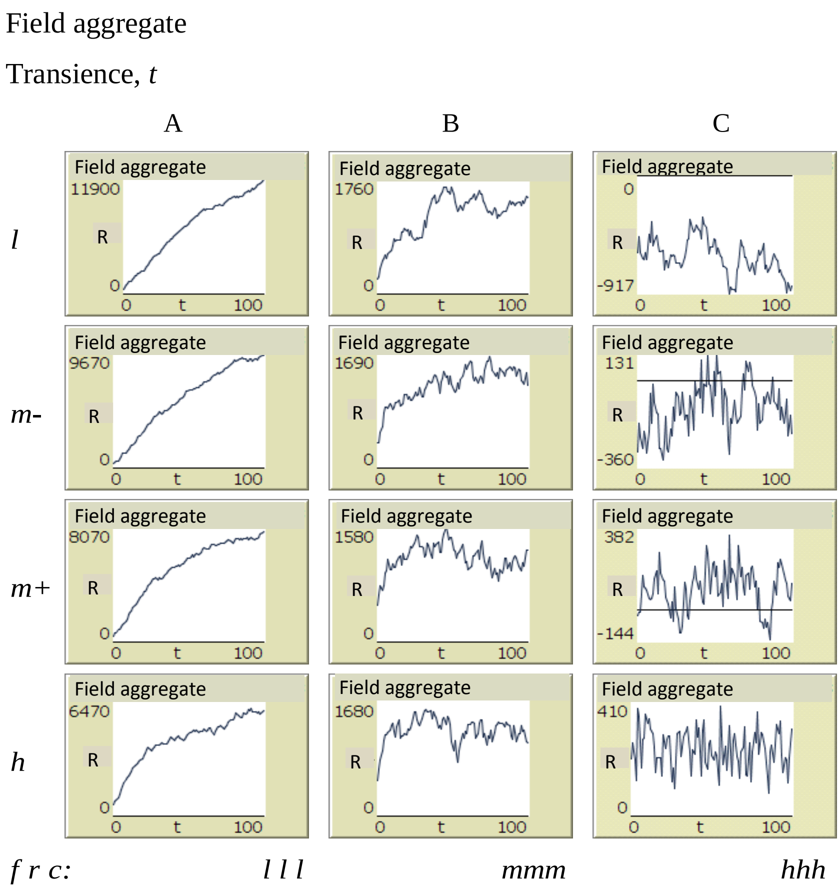


Fig. 4.19. Effects of increasing *t* on R for entire field (*flow assumption 2*)
(Graphs show effects at different levels of *frc*)

Summary of Experiment #2

Table 4.5 below summarizes the effects on dynamism and munificence caused by changes in the drivers, *tfrc*. Increases and decreases are based on the effects caused by changing the parameter settings of each variable at low and high levels for the other drivers. Rows 7 and 14 show the effects on R of changes in *tfrc* in unison (for supporting figures see Appendix A4). Following Schewe, Riordon and Stein's (2002) method of calculating heart rate unpredictability as the variance between values in 'chunks' over time, dynamism in CTS-SIM is measured as the variance in R between ticks. Munificence in terms of capacity (Dess and Beard, 1984) is measured as the aggregate value of R accumulated over time.

		Increase in:	Dynamism	Munificence
Assumption 1	1	*transience, t*	increased positive	increased negative
	2	*frequency, f*	increased positive	increased positive
	3	*flows (tf)*	increased positive	increased negative
	4	*reversal, r*	increased negative	increased negative
	5	*speed of change, c*	increased positive	increased negative
	6	*change (rc)*	increased positive	increased negative
	7	*tfrc*	positive	negative
Assumption 2	8	*transience, t*	increased positive	increased positive
	9	*frequency, f*	increased positive	increased positive
	10	*flows (tf)*	increased positive	*increased positive*
	11	*reversal, r*	increased negative	increased negative
	12	*speed of change, c*	*decreased positive*	increased negative
	13	*change (rc)*	increased positive	decreased negative
	14	*tfrc*	positive	negative

Table 4.5. Effects on dynamism and munificence of increases in each of the drivers
(Table shows effects moving from *low* to *high* levels for other drivers under flow assumptions 1 and 2)

In sum:

1) Transience, *t*, has an increased positive effect on dynamism, but the effect on munificence depends on the flow assumption.
2) Frequency, *f*, has an increased positive effect on dynamism and munificence.
3) Flows (*t* and *f* in unison) have an increased positive effect on dynamism, but as with transience, their effect on munificence depends on the flow assumption.
   The positive effect of frequency on munificence can be offset by the negative effect of transience.
4) Reversal, *r*, has an increased negative effect on dynamism and munificence.
   Recall that reversal acts as a dampener on dynamism, but also precipitates higher transience which negatively effects munificence.
5) Speed of change, *c*, has an increased negative effect on munificence, but the positive effect on dynamism depends on the flow assumption.
   Speed of change compresses time and therefore increases dynamism, and via increased reversal and transience exacerbates the negative effect on munificence.
   The dominant, dampening effect of reversal, *r*, over speed of change, *c*, is confirmed by running the same simulations at low *r*, which shows the positive effect of speed of change, *c*, on dynamism (see Appendix A4, Row 16, column F).

All of the drivers also cause significant decreases in munificence (50% to 100%) at high levels, except for frequency which causes the highest increases (around 100%), as does transience under flow assumption 2 (more than 100%).

Together, increases in the drivers, *tfrc*, cause an increase in dynamism of 10% to 40% depending on the flow assumption, and a decrease in munificence of 100%. At high levels, flows (*t* and *f* in unison) can increase dynamism by about 40% and decrease munificence by 50% (but increase it by more than 100% under assumption 2). Change (*r* and *c* in unison) can increase dynamism by about 60% (but by only 5% under assumption 2) and decrease munificence by 100%.

These simulations show that unpacking the environment provides a richer understanding of the effects of the drivers of flow and change on dynamism and munificence. Increases in the levels of the drivers, individually and in unison, increase dynamism in terms of unpredictability. However, this can be sensitive to the flow assumption and the role of *r*. Increases in the levels of the drivers decrease munificence in terms of capacity, except for frequency which works in its favour, and possibly transience, depending on the flow assumption.

So, accurate knowledge about what triggers transience would help with the task of explaining the likely effect on the emergent behaviour of the environment of a change in the level of the drivers. When the driver levels increase in unison this increases dynamism and undermines munificence. Aggregate behaviour is then reasonably consistent and simple to observe. These experiments illuminate the roles of the different drivers in the environment. Being able to change them independently and observe their effects within an interdependent system, draws out the sensitivity of the whole to small changes in the parts (see also next experiment) and to the underlying assumptions.

Although this part of the research does not attempt to analyse and explain the entire state-space, it is both useful and interesting not only for what the outcomes reveal, but also for the potential the model offers for ongoing research (Wilensky and Rand, 2007): “Even if [modelers] do not as yet have explanations for the sensitivity, it is important to point these out as directions for future research.”

4.3.3 Experiment #3:
Open search for extreme behaviours, tipping points and thresholds

Aim:

Given the outcomes of Experiment 2, I conduct an open search for extreme behaviours, tipping points or thresholds that may reveal surprises or signal the need for future pursuit. I show here the results of simulations that report R at different levels of dynamism and of reversal, *r*, again at the individual, aggregate and cumulative levels and follow this up with results that focus on the behaviour of reversal, *r*, at high flow levels and speed of change. A tension between transience, *t*, and reversal, *r*, is exposed, which paves the way for the search and discovery of a tipping point in the munificence of dynamic environments.

Settings

Experiment #3		Variables		Sample		Reporter
		r	*tfc*	*runs*	*ticks*	
3.1	1	*l, m-, m+, h*	*l l l*	*1*	*100*	R (aggregate)
	2	*l, m-, m+, h*	*m m m*			
	3	*l, m-, m+, h*	*h h h*			
	4	*l, m-, m+, h*	*l l l*	*1*	*100*	R (aggregate)
	5	*l, m-, m+, h*	*m m m*			
	6	*l, m-, m+, h*	*h h h*			

Table 4.6. Settings for Experiment #3.1

Outcomes, observations

<u>#3.1. *Investigating the tension between flow and change*</u>

The simulations below show that *the effect of reversal, r, on the munificence of R is negative regardless of the level of dynamism*. However, although reversal, *r,* drains away munificence, it cannot destroy it altogether at high flow levels and speed of change (Fig. 4.20, column C).

Field aggregate

Reversal, *r*

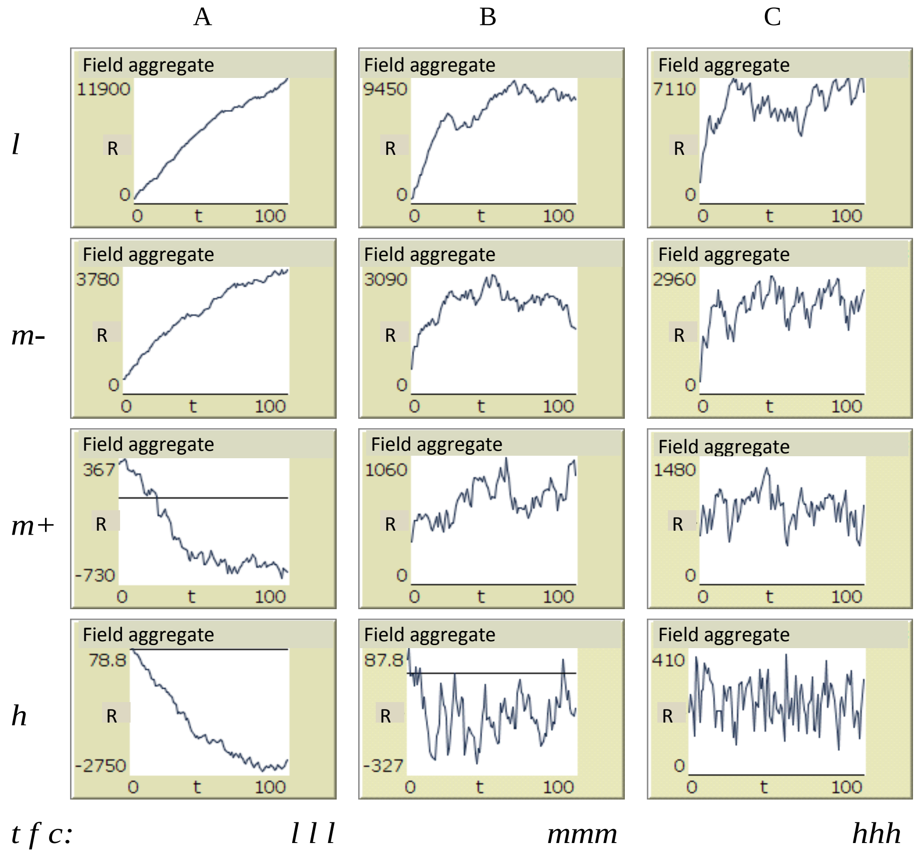


Fig. 4.20. Effects of increasing *r* on R at different levels of *tfc* for entire field

Settings

Experiment #3 (continued)		Variables		Sample		Reporter
		r	*frc*	*runs*	*ticks*	
3.2	1		*l l l*			R (random cell)
	2		*m m m*			
	3		*h h h*			
	4		*l l l*			R (aggregate)
	5	*h*	*m m m*	*1*	*100*	
	6		*h h h*			
	7		*l l l*			R (cumulative)
	8		*m m m*			
	9		*h h h*			

Table 4.7. Settings for Experiment #3.2

Fig. 4.21 below shows the effects of high reversal, *r*, on R at low, medium and high levels of *tfc* (columns A, B, and C respectively). The top row shows these effects for a single opportunity sequence, the second row for the field aggregate, and the bottom row for the field aggregate over time (cumulative).

At low levels of *tfc* (top row, column A) it is difficult to identify positive R at the individual level, except for small temporary positive 'niches'. This changes, however, as *tfc* levels increase i.e. at those levels that are of more interest for this research. It remains difficult to observe these positive effects however, until they emerge at the aggregate or cumulative levels.

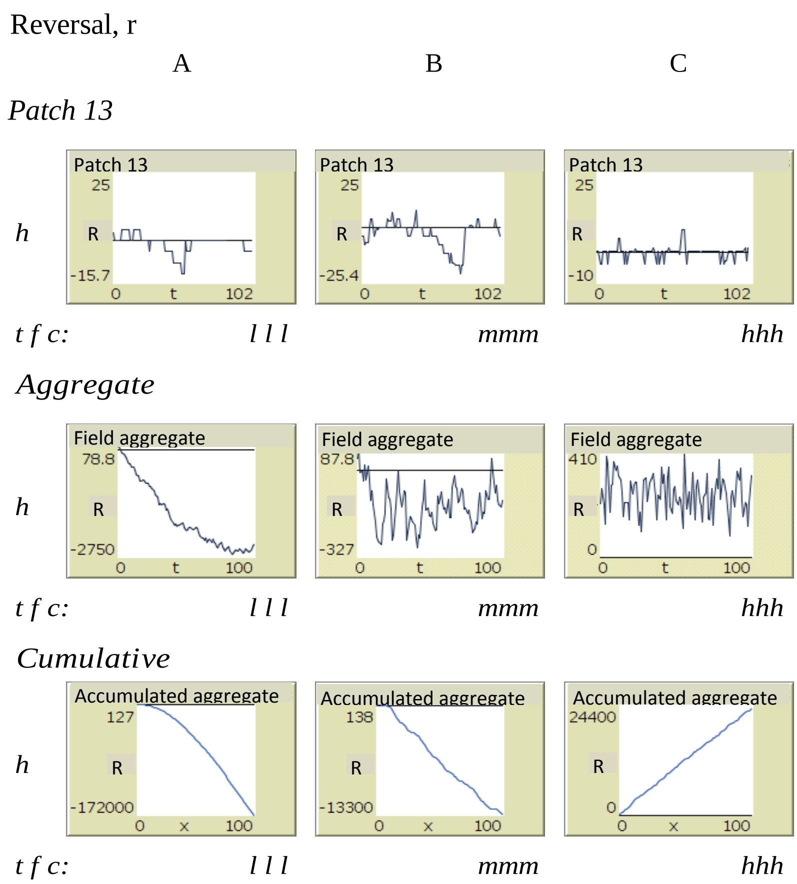


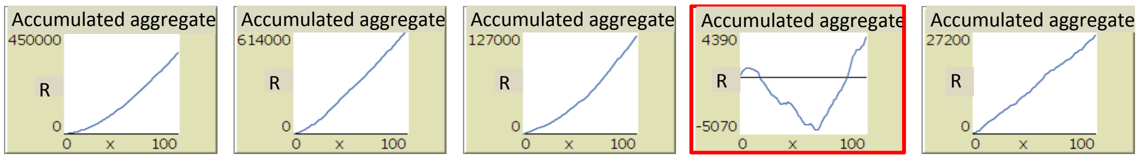
Fig. 4.21. R at high *r* and different levels of *tfc*, at all levels
(i.e. at the individual, aggregate and cumulative levels)

<u>#3.2. *Discovery of a 'rogue' environment*</u>

Given the obvious tension between the variables of flow and change (the former increasing munificence, the latter decreasing it), I finish this batch of experiments by showing the results of an unstructured search for possible tipping points in R, thresholds at which behaviour might undergo a shift or phase transition. Here I manipulate the parameter settings of transience, *t*, and reversal, *r*.

Simulation outcomes (shown below) are most useful at the cumulative level. There, at *tfrc*: *lhm*$^{+}$*m*, an exogenous environment that in some respects is highly dynamic (notably for a high flow frequency), R behaves unstably (Fig. 4.22*d*).

Cumulative

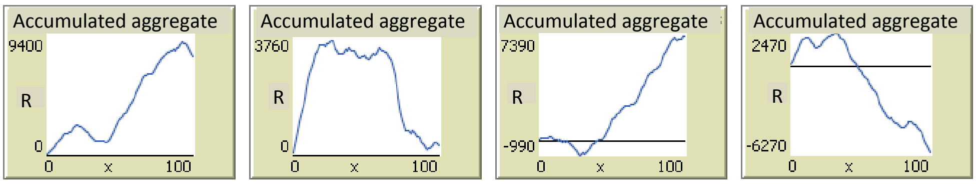


tfrc: *l l l l* *m m- l m-* *l h m l+* *l h m+ m* *h h h h*

(a) *(b)* *(c)* *(d)* *(e)*

Fig. 4.22. R at different levels of *tfrc* for the entire field over time

The munificence of R (at *tfrc*: *lhm*$^{+}$*m*), even at the cumulative level, is unpredictable. Unlike at the other settings, there is even long term unpredictability. Fig. 4.23 shows how the tension between transience, *t*, and reversal, *r*, can give rise to multifinality at the cumulative level i.e. over time. Yet minimal changes in the parameters settings for *t*, *f*, *r* or *c*, small shocks, are enough to disturb the environment sufficiently to return it to equifinality.



tfrc: *lhm*$^{+}$*m* *lhm*$^{+}$*m* *lhm*$^{+}$*m* *lhm*$^{+}$*m*

Fig. 4.23. R at *tfrc* settings of *tfrc: lhm+m* for the entire field over time

Summary of Experiments 1 - 3 and main implications

The aim of this chapter was to construct a rich, exogenously driven environment, one that builds on previous research, but in a new framework that permits more aggressive experimentation, and to investigate its behaviour in support of the overall aim of the research. Recall the distinction made between deterministic and stochastic models (North and Macal, 2007). The former are simpler and less expressive, always producing the same outputs from certain inputs by disregarding the inevitability of approximation caused by uncertainty (as is the case in the business world). The stochastic elements of the CTS-SIM environment show that the same inputs do not always guarantee a pattern will emerge (e.g. Fig. 4.23).

Results show that a few base-level variables for opportunity flows and change, because of their interdependence, are able to model a number of stylized behaviours of CTS-type environments: they change continuously and can produce sudden transitions and irregular patterns with a mix of probability and behavioural unpredictability. Even relatively small changes in the parameter settings of certain chosen micro-level elements of the environment can have surprising effects on the environment, due to tensions between them.

Results reveal patterns that distinguish the CTS-SIM environment as one that is complex, vis-à-vis one that is merely chaotic. Results using CTS-SIM show that by varying the flow, duration and change of opportunities individually, an increase in frequency, *f*, can impact the exogenous environment in an entirely different way from an increase in the speed of change, *c*. For example, establishing the relevance and utility of the CTS-SIM environment (here by testing the effects on R of varying the flow, duration and change of opportunities both individually and in combination), fits with the efforts of other researchers to lend strength to their models in this way i.e. by varying the micro level inputs.

The same goes for testing the effects on R of changing the underlying assumptions. In particular, testing the effects on R of the alternative flow assumptions reveals the potential importance of understanding the factors that dominate transience. The simple assumption that the first sign of stagnation increases the likelihood of the imminent cession of an opportunity has important implications for the environment and may be a potentially misleading oversimplification.

Simulation outcomes, for the sub-regions tested, show changes in the levels of emergent unpredictability in terms of pattern destruction and of emergent munificence in terms of capacity. This is generally only easily noticeable at certain settings and at certain levels. The CTS-SIM environment is complex and its munificence and dynamism are causally related to the level of opportunity flows and change. Increases in opportunity transience, frequency and change can each be associated with some level of increased dynamism. On the other hand, environmental munificence is conditional on the specific combination of drivers.

Although results support the feasibility of construction of an environment that fits with the stylized facts identified in this research, it would not have been feasible as a one-stop modeller to test all the potential combinations of the elements without compromising the other goals of the research. For the combinations tested, simulation outcomes lead to the following propositions.

From analysis an observation of the simulation outcomes using CTS-SIM (Figs. 4.11 - 4.17 and Appendix A4):

P1 Increased opportunity flow *into* the environment significantly increases environmental dynamism *and* munificence only at high levels of transience and change.

P2 Increased opportunity flows (transience and frequency) significantly increase environmental dynamism at high change levels (speed and direction), but their effect on munificence depends on how transience is triggered.

P3 Increased change (speed and direction) significantly decreases environmental munificence at high flow levels (transience and frequency), but the extent to which it increases dynamism depends on how transience is triggered.

P4 Increased opportunity flows and change significantly increase environmental dynamism and decrease munificence.

There are two main implications for CTS researchers. The first is that because CTS environments are complex, even small changes in opportunity flows can have surprising effects on their aggregate behaviours due to tensions between them. Hence, a useful and interesting point of departure for a better understanding of their behaviour would be to fully investigate the state-space developed here, then to continue the process by adding relevant features to it.

Further, frequency, f, clearly has a positive effect on environmental munificence (Table 4.5). So the flow of promising opportunities into the environment is a likely contributor to the successful performance of organizations operating in such environments.

However, it seems an insufficient explanation. Simulation outcomes show that frequency, f, is unable on its own to assure an overall improvement in environmental munificence. Increases in flows, tf, even ignoring the possible effects of change (Table 4.5, lines 3 and 10) only increases munificence for flow assumption 2. When change increases, the positive effect of frequency on munificence is likely to be severely undermined, unless the role of reversal, r, is suppressed i.e. the effect of an increase in speed of change, c, is predominantly positive as shown in Fig. 4.15. In other words, simulation outcomes draw out the importance of the drivers of transience and change, and the sensitivity of frequency to their levels. So something more than increased environmental munificence is probably required to answer this part of the main research question.

The second implication of these experiments is that manipulation of the drivers of opportunity flow and change enables the user of CTS-SIM to influence the aggregate behaviours of the environment. Increasing and decreasing the levels of the four drivers individually and in unison draws out consistent, measurable patterns of dynamism and munificence. Yet these are only really observable at aggregate levels and over time. This provides some initial justification for the choice of method.

These simulation outcomes also provide support for researchers who have questioned the rush to join an already multi-vocal, ambiguous and fragmented field, based purely on observations. They point to the interdependence and sensitivities of the drivers and the relevance of assumptions about factors that trigger the deaths of opportunities in CTS environments.

4.4 Facilitating evaluation: CTS-SIM environment

With the aim of inspiring critical discussion and ongoing research, the workings of the CTS-SIM environment have been carefully described in this chapter. Description was aided throughout the process by using Davis et al's roadmap for simulation research. This helped to ensure that close attention was paid to the parameters and ranges of the variables, *tfrc*, and their causal relationships with aggregate environmental behaviour in terms of dynamism and munificence.

My approach to facilitating the evaluation of the modelled environment has also included justification for using simulation, computational rigour being useful for squeezing out hidden or faulty assumptions that often escape other research techniques; justification for ABMS, especially for its virtues as a bottom-up approach; and justification for the choice of NetLogo as a toolkit for its flexibility and accessibility. NetLogo provides facilities that help overcome the three main heroic assumptions of traditional models which neglect the individual dynamics and uncertainty indispensable to modelling and theorizing human behaviour.

For the construction and observation of the environment there were no obvious weaknesses in the toolkit that would question its choice. Two facilities of NetLogo were particularly useful. The first was the random number facility, which caters for the operationalization of value ranges where specific values are not known with certainty e.g. ranges for probabilities of opportunity inception or cession. The second was the flexible GUI

(Fig. 4.24 below), which enables the modeller to add and fix variables, choose settings, to observe the nature of change on the grid, and to monitor outcomes using the plots.

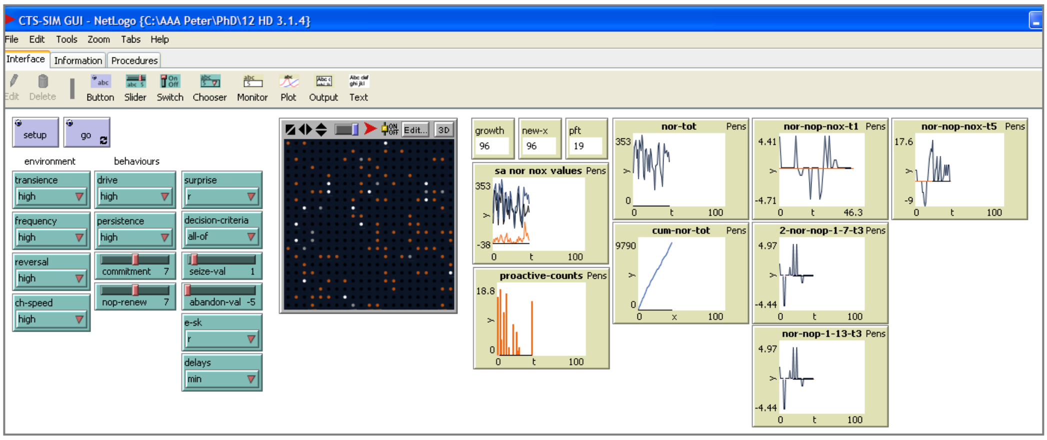
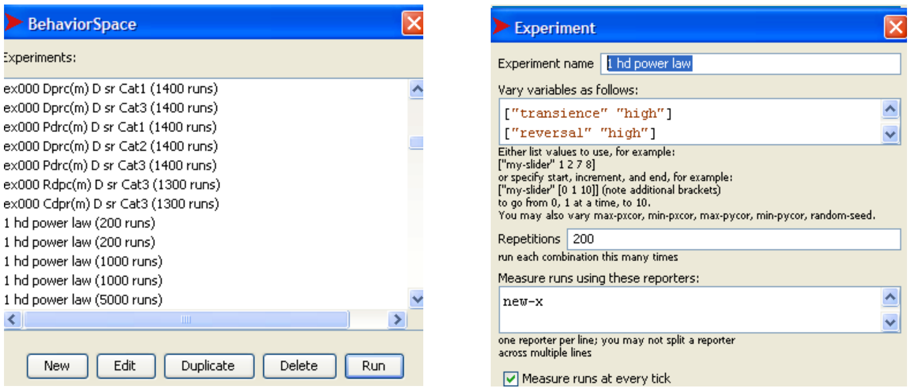


Fig. 4.24. CTS-SIM GUI showing switches, opportunity grid and output graphs

These were initial steps toward the avoidance of the heroic assumptions of homogeneity, data point independence and equilibrium discussed in Chapters 2 and 3. By including random and probabilistic elements in R, different outputs emerge from the same inputs. As will be seen in Chapter 5 many simulation runs will be required for a pattern to emerge. Characterizing and experimenting with the environment in this way, by modelling value ranges rather than precise values, helps to avoid the static, mechanistic configurations that were based on simple, linear assumptions. Doing this ‘as time unfolds’ also helps to overcome the equilibrium assumptions and assumptions commonly associated with cross-sectional data.

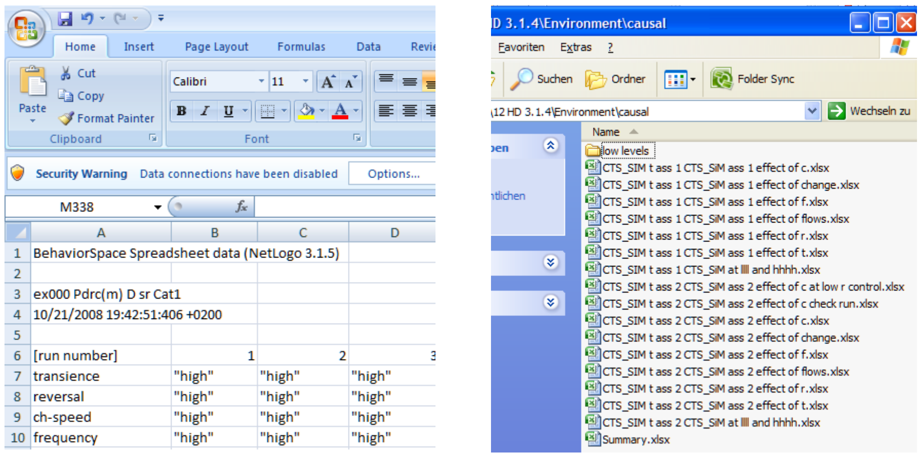
The simulation experiments are archived with the help of NetLogo’s BehaviourSpace. Fig. 4.25 shows the experiment log which facilitates ongoing editing and duplicating of experiments, and the experiment dialog, useful for future reruns and model comparison.



a) Experiment log *b) Experiment dialog*

Fig. 4.25. CTS-SIM BehaviorSpace facilities

Simulation outcomes were exported to Excel 2007 for analysis. References are generated automatically (Fig. 4.26*a*) and the data saved to hard drives (Fig. 4.26*b*).



a) Simulation data *b) Record of experiments*

Fig. 4.26. Recording and referencing of experiments using Excel 2007

To further aid the development of CTS-SIM as 'a fruitful source for theorising and developing new models', construction of the environment was guided by a number of stylized facts from empirical and case-based observations. I address the usefulness of this approach in the next section.

I finish the chapter with a brief comparison of the drivers of the CTS-SIM environment with the dimensions of Davis et al's model (2007), and pursue comparisons in the next chapter.

4.4.1 Characteristics of CTS-SIM: environment and simulation outcomes

The behaviour of exogenous CTS-type environments is deeply rooted in the literature, especially in: 1) contributions of the Austrian school, environments being in perpetual disequilibrium, 2) the early work of Emery and Trist (1965), the richly interconnected, turbulent Type IV environment, 3) more recent contributions including those of complexity theorists, Dess and Beard (1984), Sutcliffe and Huber (1998) and others, to the emergent, nonlinear, probabilistic behaviour of complex environments, and 4) Davis et al's (2007) recent conceptualization and capture of market dynamism through opportunity flows.

NetLogo's asynchronous execution of commands, and the recording of time as 'ticks', is a step toward addressing the concerns of strategic management researchers that time be treated more explicitly, as incessant, temporal and emergent rather than as a discrete, one-off formulation. This draws on the contributions of Leybourne (2006), Crossan et al (2005) and other current researchers.

The pre-action phase in the RPX framework introduced in Section 4.2 is closely aligned with established models from the entrepreneurship literature (the Intentions model and Direction of the entrepreneurial process model). At the root are opportunities, modelled as potentials that deliver unrecognized payoffs, positive or negative, which follows the observations and definitions of numerous entrepreneurship researchers, including Casson (2003), Sarasvathy et al (2003), and Shane and Eckhardt (2003).

Morris (2005) contends that opportunities in the broad environment[53] are *external* to those within the organization[54]. If the drivers of the external environment differ from the drivers of the organizational environment, to avoid the 'fallacy of composition', the exogenous CTS-SIM environment needs to be explicitly limited to the single 'organization' of agents (modelled in the next chapter). Not doing so could open the model to the suggestion that "the industry itself has no problems specific to it that are not also the problems of the component members" (Morris, 2005, p. 56). So, as indicated in Section 4.2, following Farjoun (2002), R reflects all aspects of the exogenous environment – political, economic etc. – that affect the organization.

[53] The broad environment includes socio-cultural, technological, political and economic factors such as inflation, interest rates, governmental tariffs/subsidies etc. and "changes in technology not limited to the business industry (such as the internet)" (Morris, 2005, p. 56).

[54] Internally recognized problems/challenges often referred to as task opportunities.

Driving opportunity potentials externally, through variables for flow and change, and without any influence as yet from the agents in the system, means that the exogenous CTS-SIM environment can be characterized as externally driven (stylized fact 2). However, as will be seen in the next chapter, the internal and external aspects of the environments in CTS-SIM begin to blur. The utility of the approach adopted here, is drawn out by the outcomes of the simulation experiments. The behaviour of the environment in terms of dynamism, munificence and complexity, emerges as a state and a path better understood through knowledge and observation of its drivers, *tfrc*. This is in line with the process perspective of researchers such as Barnett and Burgelman (1996), Brown and Eisenhardt (1997) and others.

The drivers of the CTS-SIM environment are constructed around stylized facts 3 and 4, the diversity and transience of opportunities and the centrality of continuous change. Modelling these variables required an approach described in the literature as artful approximation, necessary because the behaviours of the components, typical of CAS, are not certain. Basing their capture partly on random and probabilistic elements, characterizing them by ranges of possible values, represents an attempt to establish possible paths and bounds that are a source of useful information, rather than to reduce uncertainty. This approach is supported by numerous researchers (Casti, 1997; Gilbert and Troitzsch, 1999; McKelvey, 2004; North and Macal, 2007).

Modelling the drivers of the CTS-SIM environment as interactive concepts is another step toward addressing calls from researchers to progress from sequential simplifications (Chakravarthy, 1997; Eisenhardt and Sull, 2001 and others). The treatment of variables as flows also links up with approaches outside of the strategic management literature. Flows are often used to represent quantities in economics and accounting, and are ubiquitous in natural science research e.g. fluid and thermodynamics.

Construction of the CTS-SIM environment also draws out the need to differentiate between unpredictability, in terms of pattern destruction (e.g. Fig. 4.11) and inability to predict due to agent limitations. The latter are captured in the next chapter i.e. limits to agent attention and perception inaccuracy.

The result is unique simulation runs, each run producing a single possible sequence of events, from which patterns can nevertheless emerge at higher levels. This is a general concept of CAS, observed in many models e.g. Resnick's ant colony and Axelrod's neighborhood segregation model. It contrasts sharply with traditional stable and predictable models of the environment, following those of Nelson and Winter (1982), Dosi et al (1997) and others.

Simulation outcomes show evidence of emergent complexity (stylized fact 6), demonstrated by the typical nonlinear, 'roller coaster' path of R, and sensitivity to small shocks (Fig. 4.22). This is not merely path dependency, small adjustments in the *tfrc*-choosers being sufficient to throw the environment into a completely different state in terms of its dynamism and capacity.

The experiments conducted in this chapter do not fully explain the exogenous environment. The interplay of four variables for opportunity flow and change opens up a vista of behaviours deserving of deeper investigation. However, because the stated intention is to focus on opportunity-transitioning behaviour, it is possible to proceed toward that goal, with the expectation that the simulation evidence provided thus far can be utilized.

It is now possible to explore and test opportunity-transitioning behaviour in the next chapter, armed with a better understanding of the exogenous environment. Environmental dynamism and munificence can now be simulated and influenced without losing sight of the possibility of surprising effects and irregular behaviours or of the sensitivity of the system to certain fundamental assumptions.

4.4.2 Model comparison

To ensure models are 'explicit' and inspire critical discussion and ongoing scientific work, it is useful to search for opportunities for model comparison. As indicated, the CTS environment has not been unpacked in this manner before. The concurrently developed Davis et al model (2007) also deconstructs highly dynamic environments. The Davis et al model focuses on the relationship between organizational structure and performance in highly dynamic markets, not on opportunity-transitioning behaviours, and it attempts to capture environmental dimensions from the top down, not the bottom up, but it still offers interesting potential for comparison.

Here I briefly investigate the match between the approaches to constructing highly dynamic environments in this and the Davis et al model, while in the next chapter I investigate the similarities between the effects of the environmental dimensions of each model on the performance of the respective virtual organizations. There are four dimensions to the modelled Davis et al environment (Davis et al, 2007, p. 21):

1) Velocity: "the pace of opportunity flow into a given environment".
2) Complexity: "the degree to which environmental opportunities have many features that must be successfully dealt with by the organization".

3) Ambiguity: “the degree to which the key features of opportunities are difficult to interpret”.
4) Unpredictability: “the degree to which past opportunities are dissimilar from present ones and so are unforeseeable”.

Complexity and ambiguity are not treated as drivers of the exogenous CTS-SIM environment. Important features of complexity are left to emerge from the interactions of the variables, *tfrc*. So there is no attempt to capture complexity from the top down. This approach follows stylized fact 6. Also, for CTS-SIM ‘ambiguity’ is not viewed independently of the organization. Instead, ‘difficulty in interpreting opportunities’ is captured in the next chapter of CTS-SIM in terms of agent skills and perceptions. This approach follows stylized fact 2.

So the above two dimensions of the Davis et al modelled environment are, justifiably, not treated as drivers of the CTS-SIM environment. However, velocity (‘pace of flow into the environment’) and unpredictability (in terms of pattern destruction, not the inability to predict) are. Davis et al (2007, p. 22) name the Internet bubble as an environment with a high velocity of opportunities and view it as “a key dimension of market dynamism because it influences the nature of major organizational activities like strategic decision making”. The pace of opportunity flow *into* the CTS-SIM environment can be influenced by the frequency variable, *f*. This is shown in Fig. 4.14*b* and *e*.

Davis et al (2007) also note the role of lack of pattern in highly competitive growth markets. Lack of pattern, or pattern destruction, emerges in the exogenous CTS-SIM environment and is shaped by the interdependence of the variables, *tfrc*. This can be observed in Fig. 4.11.

Hence, the two approaches to deconstructing the environment are similar in certain respects, specifically in terms of pace of opportunity flow into the environment and environmental unpredictability in terms of pattern destruction. But there are two key differences. One is drawn out by the bottom-up versus top-down treatment of complexity. The other is a different treatment of ambiguity. For CTS-SIM, difficulty interpreting the environment is an agent issue. The differences can be explained by the goals for modelling the environments, the Davis et al model not specifically attempting to model the externally driven exogenous environment.

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5. CTS-SIM: OPPORTUNISTIC AGENTS

"We hijack ships every opportunity we get."
Sugule Ali, pirate commander

Having examined some of the causal relationships between the drivers of highly dynamic environments and their emergent behaviour in line with calls for their conceptualization as made up of opportunity flows and change, I now turn to the dynamics of the opportunity-transitioning process.

The presentation of this chapter also follows the Davis et al roadmap, though again the steps were not undertaken sequentially as it might appear here: research questions, construction and verification, experimentation and validation. The chapter also develops the main RPX framework further (Section 5.2), establishing a platform from which a more coherent perspective of the target CAS emerges and to which components can be added in future.

5.1 Research questions

The main question I pursue in this chapter, and the question that guides this research, is *'How does distributed, opportunistic behaviour in dynamic modelled CTS-type environments, likely to produce unreliable agent performance, benefit the agent 'organization' in general?'* This is now partly informed by the modelling and simulation outcomes in the previous chapter.

As in Chapter 4, this question also gives rise to three underlying questions:

1) What behaviours and attributes are significant and important for an interesting and useful representation of opportunity-transitioning behaviour in CTS-type organizations?
2) How do the chosen variables affect the performance of the simulated organization?
3) How sensitive is the behaviour of the system to the important model assumptions?

So the intention now is to investigate whether the environment can be inhabited by a simply structured organization of individual agents, which enables them to 'tackle problems at the local level', but which can call upon a central authority to constrain and guide it. As indicated, the agents need to be highly interconnected, heterogeneous and sub-rational. They should form their own individual, imperfect perceptions and act on them in spite of their limitations, and hence make surprising errors. Surprise, error and discontinuity should be pervasive components, though they should not prevent success from emerging. Outcomes should somehow be generated that are internally and externally driven and the result of sheer luck.

To these ends, I set out to populate the CTS-SIM environment with agents using these important characteristics to guide model construction, though in a new framework that permits more aggressive experimentation. It remains a condition of the research to address the difficulty traditional research methods have in capturing uncertainty and the effects of complexity and change over time. As indicated, this is expected to be more useful and interesting to users when the variables can be controlled and manipulated using ABMS, given the large amount of data generated.

Following the construction of the model extensions in this chapter, I proceed with a further three batches of experiments. In Experiment #4, I test the *effects on performance of each of the four chosen agent behaviours* under three different conditions of dynamism and munificence, by varying the parameter settings. The aim is to squeeze out lack of precision in terms and definitions that could provide needed support for CTS, and to discover surprising behaviours that contribute to the further development of CTS.

In Experiment #5, I arrive at the intriguing question regarding the role of individual opportunism in successful organizations. I test the *effects on performance of opportunism based on different tolerance levels for opportunity seizure and abandonment*. Here I again vary the settings under the same environmental conditions as before.

In Experiment #6, I extend the model to account for model sensitivity to *delays* in payoffs, test constraints on agent *decision-making freedom*, and search for aggregate *patterns in transitioning behaviours*.

5.2 Construction and verification

As with the environment, I list a number of further stylized facts below that relate to CTS-type systems. These too are intended to increase model transparency, to act as a guide to model construction, and to inspire critical discussion. This is because the relevance and usefulness of CTS-SIM is partly an issue of how well it facilitates discussion and ongoing scientific interest. As noted in Chapter 3, the guidance provided by numerous stylized behaviours helps to restrict the stochastic processes that might have generated the data that display them (Windrum et al, 2007).

Stylized fact 7: *Perception-based decision-making*
No simple answer has been found as to how entrepreneurs recognize patterns, or perceive and exploit opportunities. But there is a large body of evidence on managerial decision-making linked with cognitive studies which supports decision-makers' use of filters, constructs and measures based on perceptions of the environment rather than on 'reality' (March and Olsen, 1976; Mintzberg, 1978; Tversky and Kahnemann, 1986; Pettigrew, 1987; Krueger, 2003 etc.).

Stylized fact 8: *Managerial surprise, error and uncertainty*
Also from the above literature streams, stems a general acknowledgement of peoples' limitations (due to lack of knowledge, computational ability, and inability to consider more than a few factors simultaneously). Decision-makers appear willing to base their decisions on personal sufficiency rather than objective rationality. An outcome is the pervasiveness of surprise, error and discontinuity in complex systems (March, 1994; Cunha et al, 2006) which can be linked to the shift away from the neoclassical assumption of equilibrium dynamics. This does not prevent successful performance. The important findings of Mezias and Starbuck (2003) confirm both a lack of need for agreement among decision-makers or complete or accurate current knowledge of situations for effective action.
The pervasiveness of surprise and error is an outcome that can be linked to the theory of limited attention (Gifford, 2003) which follows research that goes back to early studies of managerial uncertainty (March and Simon, 1958). Without these theories, without disequilibrium, there is no role for the entrepreneur-manager.

Stylized fact 9: *Organizational simplicity and interdependent, distributed decision-making*
There is a strong association in the literature between the principles of CAS and the behaviour of organizations. These principles apply to CTS environments: they are characterized by large numbers of interdependent stochastic elements (stylized facts 5 and 6). They also apply to CTS organizations: they operate in open, social contexts, characterized by large numbers of interdependent, stochastic decision-making elements. Implicit in the notion of strategy as opportunity pursuit for CTS (i.e. the pursuit of payoffs, stylized fact 11) is the ability of strategists to deploy resources 'at each moment to their most

urgent uses' and the realization that decision-makers are not committed to avoiding uncertainty. This has spawned a stream of literature into the role of dynamic capabilities and a focus on action rather than planning.

This in turn is facilitated by minimal structures, which links to the large body of multidisciplinary research into CAS. Structural simplicity implies a flatter hierarchy with greater speed and autonomy of action, a design that enables people in organizations to tackle problems at the local level, but with just enough guidance from the central authority for quick response and temporary advantages to emerge. This enables the generation of novelty and ceaseless recombination that fits well with strategy as opportunity pursuit.

Stylized fact 10: *Managerial individuality*

Organizations are typically populated by individuals who, in spite of commonalities, are all different, whether in their perceptions of the environment, their goals, drive, perspectives of time, and so on. The very name 'multi-agent systems' research is testimony to the recognition researchers give to systems with many interacting components that possess some level of freedom and autonomy i.e. are able to perceive their environment and react to changes in it, depending on their goals. Note that organizations, even those with distributed decision-making, generally possess a central leadership authority to guide its direction and shape its structure, so that decision-making autonomy is one of degree, unlike in many other CAS.

Stylized fact 11: *Organizations pursue payoffs*

The idea that profit-oriented decision-making agents are the driving force of market processes, not the consumers or owners of the resources, is central to several literature streams. The logic of opportunity pursuit has displaced the conventional wisdom that decision-makers avoid uncertainty. Alertness, a stylized fact stemming from the Austrian school, has long been regarded as the key requirement for successful entrepreneurial action. This is followed by probes for opportunities (decision-making theorists) and, as circumstances dictate, jumping into markets, building on successful forays, shifting flexibly among novel opportunities and ceaseless recombination of portfolios (CTS theorists).

Stylized fact 12: *Opportunity superabundance*

The interaction of many stochastic environmental elements (stylized fact 5), perception-based decision-making (stylized fact 7) and agent limitations expressed as managerial error and surprise (stylized fact 8), typically give rise to the phenomenon of CTS decision-making in terms of choosing between many options. This has been explained by recent developments including technological change, globalization, lower barriers to entry etc., and is captured succinctly by an Internet executive: “I have a thousand opportunities a day; strategy is deciding which 50 to do.” (Eisenhardt and Sull, 2001, p. 108).

Stylized fact 13*: Success at the interface of internal drivers, external drivers and luck*
The literature streams that have 1) characterized environments as made up of elements that interact among themselves (stylized fact 2), 2) shown that decision-making individuals are key to successful entrepreneurial action (stylized fact 11), and 3) characterize both environments and organizations as uncertain and nondeterministic (stylized facts 5 and 8), have been successfully merged in CTS i.e. successful performance is driven externally, internally and by chance.

Again, there are characteristics that apply to CAS in general, to which CTS-type systems have been observed to belong:

Stylized fact 14: *Blurring of environment and agents*
A reason for the shift away from a neoclassical view of the firm was the growing dissatisfaction with a firm partitioning of environment and organization, and broad recognition of the need to develop an inclusive typology of entrepreneurial opportunities. Opportunities might be created, discovered or recognised, depending on the conditions. Each is empirically ‘valid’ at some stage of market creation.

Stylized fact 15: *Emergent system complexity*
From the bodies of research into CAS and MAS (multi-agent systems), *system complexity emerges through interdependent, stochastic, probabilistic structures and events* with properties that differ from the component parts and that escape parsimonious description. Here system complexity emerges from environmental complexity (stylized fact 6) and organizational complexity (stylized facts 7 - 15).

I began the modelling process in the previous chapter with the construction of an environment that models each of the chosen stylized facts – a large and diverse set of opportunity potentials, driven externally by continuous, stochastic flows and change, which gave rise to nonlinear path dependencies due to the interactions of *tfrc*. In completing the construction of this version of CTS-SIM in this chapter, I explicitly take on board the above regularities (stylized facts 7 - 15). This is a lengthy list, but a model unable to draw on (a preferably long list of) stylized facts can become a target for harsh criticism.

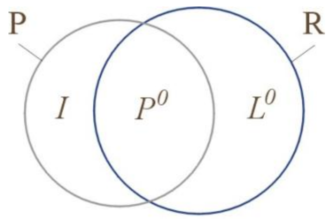
Still following the Davis et al roadmap, this section consists of five parts: 1) building on the RPX construct, 2) quantifying the significant variables for the behaviours and decision-making strategies of the agents, 3) demonstrating the logical flow of the model extensions, 4) addressing the main underlying assumptions and 5) verifying the extended model.

5.2.1 Construct and definitions

RPX framework continued

Having developed the externally driven environment, I now progress to the perceived environment, identifiable by ‘a variety of fuzzy perceptions’, and an enacted environment, identifiable by acts of agent construction. Thus, having begun the modelling process with the ‘realistic’ notion of opportunities, opportunities that can be recognized, discovered or created, I now account for how they are perceived and acted upon, a matter for the decision-making agents.

The pre-action phase of RPX (again Fig. 4.1. below) introduced R, the exogenously driven environment, and P, the perceived uncertain world. Indeterminacies arise when elements of opportunities are perceived but unrealistic (imagined, I) or when realistic but unperceived (initially latent, L^0).



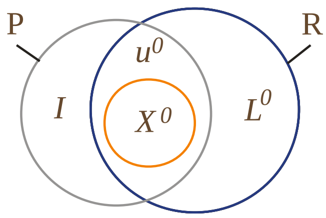
P = opportunities perceived, R = ‘realistic’, I = ‘imagined’, P^0 = initial potential, L^0 = initial latent

(Fig. 4.1. RPX: pre-action phase)

In CTS-SIM, agents’ perceptions, P, if acted upon, generate payoffs, X. Here P is considered to be a reflection of managerial perceptions, adjusted for what decision-makers consider the organization to be capable of by way of action and response i.e. if they consider the organization incapable of acting on P, then P falls away.

The exploitation process is also characterised by indeterminacies (inaccuracies, inefficiencies and inattention), the extent of which depends on the agents’ skills of perception and execution. The greater the accuracy and timeliness of agent perceptions, the greater the degree to which P intersects with R.

At this early point in the exploitation process, the overlap of R and P (R ∩ P) represents potential for payoffs, that which is perceived and realistic. This is one source of potential, P^0. A chief determinant of the level of exploitation of this potential would be the agent's[55] execution skills, *e-sk*. Exploitation (payoff) is represented in Fig. 5.1 as X^0. The residual is initially unexploited, u^0, due to imperfect skills.



P = opportunities perceived, R = 'realistic', *I* = 'imagined', X^0 = initial payoff, u^0 = unexploited, L^0 = initial latent

Fig. 5.1. RPX: initial action phase

In short, CTS-SIM follows the directional opportunity exploitation process, 'existence' → discovery → exploitation, as R → P → X.

So R, the exogenous 'realistic' environment, now takes the form of a potential that may, for the agent, be partly known, unknown and unknowable. In fact, agents of the organization (entrepreneurs, decision-makers, strategic business unit leaders), may partly or fully perceive R and act on that, or not, as the case may be. They might, however, miss R completely due to ignorance (Sarasvathy et al in Acs and Audretsch, 2003). Missed opportunities, not acted upon, are addressed shortly under uncertainty.

It will become clear that agents perceive and exploit their own opportunities on the grid, as do their human counterparts. The payoff from an opportunity acted upon is the product of the payoff potential, R (on that particular patch) and the particular agent's skills, *e-sk*. This is a reflection of 'individual' performance.

For the 'organization' of agents on the grid, the total payoff (performance) is the sum of the individual performances. Hence, in the case of 'seen' opportunities:

For CTS-SIM: $$\mathrm{X} = esk.\sum_{1}^{n} \mathrm{R}_1^a \qquad (1)$$

n = grid size, and *a* represents additive-type opportunities[56]

[55] Although I occasionally refer to the agent in the singular, CTS-SIM simulates the behaviour of many agents/turtles.

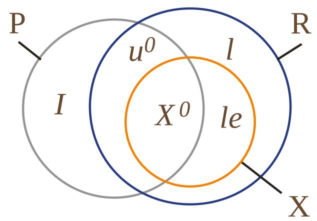
[56] Recall (Chapter 4, Section 4.2.3) that aggregate opportunities on the grid is equal to the sum of the individual opportunities.

It will also become clear that aggregate performance, although the sum of all the agents' payoffs (achievements) is not the sum of their individual efforts. Agents doing their best may or may not perform well. Luck and the environment can have a bearing. From this perspective, the whole is not necessarily the sum of the parts. To that extent, the model follows the expectations of those researchers who argue that this is the whole point of ABMS.

Agent action, because it follows P, can take place in CTS-SIM whether an opportunity exists at the time or not. However, because R changes at the next tick, a payoff may yet accrue. To what extent should such a payoff be regarded as internally vis-à-vis externally driven? Clearly both internal and external drivers are prerequisites. This is the blurring of the CTS-SIM environment.

Integrating surprise into the RPX framework

Another source of potential besides P^0 (Fig. 4.1) lies within L^0. Since agents are executing on R, there is a possible *unforeseen benefit* or 'latent effect', *le*, in the presence of L^0. One would expect that simply being in the business of opportunity exploitation could well generate unforeseen results. The total payoff to the agent, X, ought to be the sum of X^0 and *le*. The total residual amount, exploitable but unexploited at the end of the process, would then be the sum of u^0 and *l* (Fig. 5.2).



P = opportunities perceived, R = 'realistic', *I* = 'imagined', u^0 = unexploited, X^0 = initial exploited, *le* = latent effect, *l* = latent

Fig. 5.2. RPX: action phase

In an unpredictable environment, regardless of whether agents *underestimate* opportunity potential (P < R as in Fig. 5.2 above) or *overestimate* it (P > R as in Fig. 5.3 below), there is a possible *net unforeseen effect*, *le*.

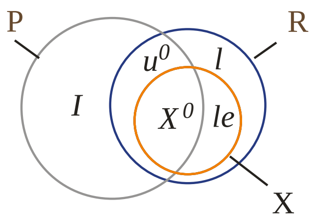


Fig. 5.3. RPX: action phase showing agent overestimation (P > R)

As indicated, surprise and error should be of central interest to studies of strategy, particularly in the CTS context. The Austrian school pointed to regular surprises as a feature of the opportunity exploitation process (stylized fact 8). This is due to the indeterminacies referred to above which lead to outcomes better or worse than expected. "[S]urprise is a pervasive feature of complex systems, not an exogenous factor amenable to removal." (Cunha et al, 2006).

The RPX framework reveals three sources of surprise, S. They are *I*, u^0 (both negative) and *le* (positive), each being an unexpected outcome. There is a strong relationship between P, X and S. Agents acting on P are interested both in maximising X and minimising S. These organizational behaviours are commonly observed and well-documented. Menger (1871) first linked 'a good thing' with a human need and knowledge, a causal connection between the two, and a sufficient command of the thing. Dutton and Jackson (1987, p. 80): "A situation where the likely outcomes are perceived as positive... and deemed as within one's control would be categorized as an opportunity."

One might reasonably argue, therefore, that surprise derives from the difference between perceived and actual payoff, hence:

For CTS-SIM: $S = X \pm P$ (2)

It is useful to distinguish surprise from error using the RPX framework. If error is taken to be the 'estimated difference between observed and true values'[57], then there are two sources of error, u^0 and *l* .If it is taken to be the 'difference between estimated and true values'[58], there is a third source, *I* (Fig. 5.4).

[57] Error definition 1: 'The measure of the estimated difference between the observed or calculated value of a quantity and its true value.' (Oxford English Dictionary).
[58] Error definition 2: 'The difference between a computed, estimated, or measured value and the true, specified, or theoretically correct value.' (Source: Federal Standard 1037C, MIL-STD-188, http://www.its.bldrdoc.gov/fs-1037/fs-1037c.htm, Accessed October, 2007).

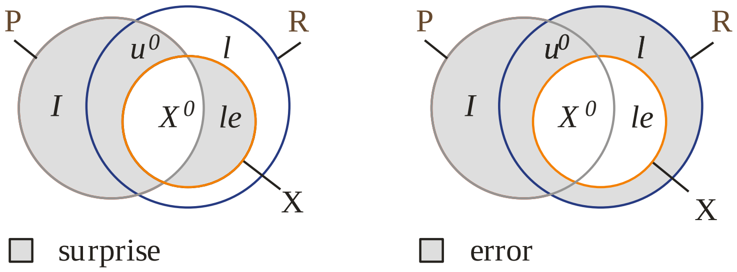


Fig. 5.4. RPX: surprise and error

The sources of surprise, unlike those of error, might well offset one another in practice, reducing their overall effect. Note that these are *sources* of surprise, not surprise itself.

RPX as shown above is a simplified depiction of the main construct underlying CTS-SIM. The subsets become fuzzier when the model 'comes to life', time becoming more incessant, flows more interactive and the elements more integrative.

Note also that the above relates to the *action phase*. Once over, agents have time to adjust their perceptions for the future i.e. in CTS-SIM, to prepare themselves for the next 'tick'.

Performance payoffs, X

CTS-SIM agents seize and retain opportunities that they expect will yield future payoffs. I treat perception, P, as a reflection of beliefs about discounted future payoffs, not always expected to yield immediate payoffs. The entrepreneur's goal is to maximise the discounted expected value of all current and new ventures over time (Gifford, 2003).

So performance for CTS-SIM is the sum of all currently retained opportunity payoffs, X, accumulated over time. Payoffs from each individual opportunity are based on RPX equation (1). Growth can therefore be understood in terms of increases in the number and value of opportunities (Nadkarni and Narayanan, 2007). Since performance is a reflection of the quality of agent alignment with the environment, agent performance, X, in CTS-SIM, should be a reflection of alignment with the exogenous environment, R.

Note that performance in practice can be represented by growth, profitability, survival, and other standard indicators, and by non-financial indicators (Chakravarthy, 1997). Focussing in the model on the accrual of payoffs, financial or otherwise, is a convenient simplification, permitting capture and comparison of behaviours and strategies over time and focussing away from short term indicators (Dosi et al, 1997). Basing performance of the CTS-SIM organization on the accrual of payoffs, X, is a simplification because it ignores liquidity, and abstracts away from the time value of money. In practice, an organization may not survive due to cash flow problems at a point in time, but this might be a poor reflection of its performance *over time*[59].

A decision-maker who expects a discounted present value of £10m from future payoffs will choose it over an opportunity with a perceived present value of £5m. Selection depends on the agent's perceptions, P. Regardless of whether the first payoff accrues as expected (depending on S, RPX (2)) or whether it is higher than the first payoff might have been from the alternative opportunity, the decision as to whether to persist with the opportunity or 'change horses' then depends on the agent's motivation, drive, commitment etc. These behaviours are also key to the opportunity-transitioning process.

Agent behaviours: drive, persistence, perception and initial commitment

Of the numerous candidate variables[60] that appear to most significantly capture the behaviours associated with successful decision-making, four umbrella behaviours emerged. First, there is the observation that successful individuals are on the constant lookout for new opportunities, 'always alert never complacent'. This relates closely to their most distinctive behaviour, that of intent, so for whatever deeper need or cause (whether for profit, social recognition, personal satisfaction, or some combination of these), they generally expose themselves as highly *driven*. They embrace change. Drive is what distinguishes them from ordinary decision-makers[61].

I regard drive as a posture taken toward *new* opportunities. Its equivalent in the case of *retained* opportunities would be *persistence*. So drive impacts the seizure of new opportunities (i.e. that are highly perceived), while persistence impacts the retention of currently exploited opportunities (i.e. that are poorly perceived).

Both drive and persistence are behaviours that shape how perceptions are acted upon. Yet agent alertness and eagerness is as much a feature of the pre-action search phase of opportunity-transitioning as of the action phase. Agent behaviours that shape how agents perceive are a measure of their pre-action alertness and eagerness and possibly equally significant to the ongoing exploitation process. Hence, the *renewal of perceptions*, particularly in highly dynamic conditions, could be another key behaviour that distinguishes CTS-SIM agents from ordinary decision-makers.

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[59] I consider the latter to be of most interest in this research. I also leave other financial effects, such as inflation, to future model extensions.
[60] Wickham (1998), for example, ascribes entrepreneurial behaviour to assertiveness, receptiveness to new ideas, inquisitiveness and willingness to seek out information – all in the absence of any special endowment of intelligence.
[61] For Wickham, successful entrepreneurs are learners i.e. are always aware of their skills/limitations, and receptive to improving/ developing them.

At this point, one therefore envisages the successful entrepreneur-manager in a highly dynamic environment transitioning among opportunities so rapidly and incessantly that at times there may be very little continuity. However, in practice, investments in new opportunities are generally pursued for a time and a reason, at least until the point at which decision-makers are forced to acknowledge otherwise. For CTS-SIM, therefore, new opportunities are given a chance to generate payoffs and are abandoned only when agents believe pursuit is no longer worthwhile, or perceive better alternatives. A variable for this *initial commitment*[62] to a newly seized opportunity, in part captures agents' attempts to establish a measure of continuity and control over the environment. Commitment is an inherent part of what Durand (2006) describes as the orientation and transformation of resources into a combination that adheres to a 'logic of action'.

In sum, CTS-SIM focuses on four agent behaviours for timing the exploitation of opportunities, those expected to impinge most significantly on performance.

1) Drive, d: probability of opportunity seizure of best-perceived opportunities.
2) Persistence, p: probability of abandonment of worst-perceived opportunities.
3) Perception renewal, p^r: regularity of updating opportunity perceptions.
4) Initial commitment, c: period of commitment to newly seized opportunities.

I use the acronym dpp^rc for the group of agent behaviours, as with the acronym *tfrc* used for the group of environmental dimensions in the previous chapter.

Agent attributes: execution skills, surprise and uncertainty

The above groups, dpp^rc and *tfrc*, are therefore integrated into the model, but without compromising on three further significant features of CTS-type systems. Following the RPX framework, once an opportunity has been seized, the initial payoff depends on how well it is executed. Execution skills, *e-sk*, a fraction of '1', tend towards '1' as the skill level increases (see next section). If the value of an externally driven opportunity potential, R, is known, and execution skills can be estimated for simulation purposes, then the payoff to the agent, X, can be derived using RPX (1).

At this point, it would be possible to run simulations that allow for some control over dynamism, via *tfrc*, and to observe the effect on agent performance, X, of behaviours dpp^rc. However, there is no way of knowing how agents would form their beliefs or preferences, P,

[62] For Ghemawat (1991) commitment acts as a dynamic constraint on strategy – the organization's way of looking into the future – caused by lock-in, lock-out, lags and/or inertia. In CTS environments it is not possible to look very deeply into the future, hence this might be considered more of a tactical than a strategic behaviour.

without some suitable value for it. As Kruger suggests, entrepreneurs appear to identify opportunities based on environmental signals. A potential variable, therefore, would be 'perception skills' that shape perceptions, P, arrived at in order of preference. However, the literature is not supportive of any way of measuring P. This might partly explain why a model of this nature has thus far eluded researchers simulating organizations as CAS[63].

The RPX framework points to another route. Given the assurance of regular surprises in highly dynamic markets (Austrian economists), a variable for surprise, given X, offers a platform from which to generate values for perceptions, P, using RPX (2). In order to establish the level of exploitation of the environment, R, the pathway to agent performance, X, is via the surprise variable, S. Cunha et al, 2006, p. 319: "[S]urprises should not be taken as dichotomous on/off phenomena but rather should be considered as a variable with a threshold." This is significant for CTS-SIM and for the experiments conducted and described in this chapter.

Now CTS-SIM can be used to attempt to simulate the behaviour of agents in highly dynamic markets since it is possible to reconstruct decision-making agents' perceptions via surprise, S, and performance, X. However, there is still no way of knowing which opportunities agents might actually 'foresee'. From the perspective that opportunities only emerge where there is asymmetric information among individuals, agent uncertainty and risk aversion are still missing features of the model. Simulations would ignore Gifford's contribution on the role of human capital investment. Since agents might well miss R completely due to ignorance[64], there is a need to integrate one final feature into the model: agent uncertainty.

This is not difficult to build into CTS-SIM, if agent uncertainty in terms of limited attention, is measured as the 'degree of awareness' of the opportunity field. Agents need only be partially aware of the field. As a group or organization, they do not attend to all opportunities at once. Agent uncertainty therefore affects the quality and quantity of opportunities acted upon, and hence missed. Low uncertainty increases the probability of high exploitation (in the presence of high execution skills and a munificent environment, for example), while high uncertainty decreases it. In simple terms, agent perceptions capture the

[63] In a recent attempt to quantify perceptions, Parker (2006) asserts that entrepreneurs adjust their beliefs/expectations at an average rate of 14% - 21% depending on their age. Unfortunately for the purposes of CTS-SIM, this finding was based on the proposition that earnings expectations relate to effort in terms of the number of hours worked, a tenuous connection made in the neoclassical tradition.

[64] Dekel, Lipman and Rustichini (1998) differentiate between not foreseeing and not understanding (the latter is unaware of being unaware) by using the example that a doctor 60 years ago might have understood what AIDS is without foreseeing its possibility.

value of the perceived environment, while agent uncertainty places limits on the size of the perceived environment.

There are three final points worth noting. First, agent uncertainty refers to the level of uncertainty across the entire opportunity field, and is therefore an aggregate of individual agent uncertainty. How this can fit with individual limits to attention is explained in Section 5.2.4.

Second, agent uncertainty applies to what is unknown, outside of the field of attention and hence outside of perceptions, P. For the RPX framework, it would be part of the residual amount, l (Fig. 5.3). This is different from u^0, which denotes the unexploited portion of what is perceived and realistic i.e. falls within the field of attention.

Third, agent error is not specifically built into the model, the expectation being that it will emerge as a system attribute during verification testing (as it inevitably does, see Section 5.2.5).

Summary

Without the above behavioural variables (dpp^rc) and agent attributes (execution skills, surprise and uncertainty), the model would compromise on the general acknowledgement of peoples' limitations stemming from a lack of knowledge and skills. Their inclusion helps to avoid running the risk of being linked with the neoclassical assumptions of equilibrium dynamics. Capturing these variables confirms that agent action in CTS-SIM, *if* successful, must be so regardless of whether the agents' abilities or knowledge of the environment are accurate (stylized facts 8 - 9).

Without drive or persistence, it would be impossible to begin to simulate entrepreneurial action. Drive influences the seizure of new opportunities, persistence the retention of currently exploited opportunities (stylized fact 9). Ignoring perception renewal could compromise on the role of perceptions in the opportunity-transitioning process, and hence the huge body of evidence on managerial decision-making dating back to March and Olsen's seminal work over thirty years ago (stylized fact 7). Without initial commitment, it would not be possible to model continuity or 'logic of action', a sense of direction, which characterizes how agents are 'observed' to flexibly shift among novel opportunities (stylized fact 11).

Again, it is not to say that researching the behaviour of fewer variables, perhaps more deeply, would not also be potentially useful. Rather, these variables are, for ontological purposes, a 'minimum requirement' i.e. for a meaningful representation of fast, error-prone opportunity-transitioning in CTS systems.

As with the environment, CTS-SIM is intended to enable the user to observe the effects of all the behaviours in unison. This is a potentially more useful and interesting way of modelling CTS-type systems. But it also allows users to ‘fix’ certain variables and focus on others. The advantage of capturing and then fixing certain variables, depending on the aim of the experiment, is that it does not permit the researcher to idealize simulation outcomes, nor compromise on causal clarity. It is a more transparent, possibly more ‘honest’ approach, to conducting social science using simulation.

5.2.2 Quantification

Parameters

The *choosers*, *sliders* and *switches* already in operation for the environment are now augmented by those for the agent behaviours and attributes described in the previous section. Where appropriate, the settings match those of the environmental dimensions i.e. there are seven settings, low to high (*l, l+... h*). This level of calibration is again an attempt to balance the need to detect the effects of small changes in settings, with practical considerations.

In certain situations there was a need for a different treatment (i.e. for p^r and c).

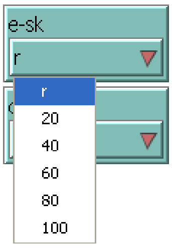


Fig. 5.5. *e-sk* choices (r = random)

Capturing the likelihood and extent to which the above variables, dpp^rc, affect the performance, X, of the agents, entailed the same two-step process as that for capturing the impact of *tfrc* on R in the previous chapter i.e. that of first drawing a random number and then, depending on the parameter setting for the variable, assigning it to that variable.

Agent drive, d

Agent drive being the criteria for opportunity seizure, the *d* chooser permits control of the probability that opportunities *above* a threshold value will be *selected*. Like *tfrc*, the higher the setting the higher the probability of selection.

Agent persistence, p

Persistence being the criteria for opportunity retention, the *p* chooser permits control of the probability that opportunities *below* a threshold value will be *abandoned*. The process mirrors that of *d* in all respects, but whereas the *d* chooser influences the seizure of the perceived highest qualifying opportunities, the *p* chooser influences the abandonment of the perceived lowest qualifying opportunities.

Given the built-in randomness, these ‘commands’ are fuzzy, so both choosers should be understood as guides to the level of agent inclination (motivation), not as fixed rules or commands.

Agent perception renewal, p^r

Whereas the *d* and *p* choosers control the parameters that shape agent actions, the p^r slider controls those that shape perceptions. As indicated, CTS-SIM simulations are progressed as part of a synthesis of clock and event time in units called ticks. Just as slider settings for transience, *t*, influence the duration of opportunities, so slider settings for perception renewal, p^r, influence the delay between renewals of agent perceptions, P. Renewals range from every tick (decision-making opportunity) to every seventh tick.

Technically, the model behaves as follows. Just as R, S and X all have unique values for each cell, so P has a unique status. At a high p^r setting, agents renew their perceptions at each tick. A P status of 1 signals the renewal of the value of P (where P = X - S (2)). The P status remains at 1 throughout the simulation (P follows X minus S), agents renewing perceptions every tick. At a low p^r setting, agents only renew their perceptions every seventh tick. The P status is set to 7, and advances tick-for-tick from 7 down to 1, P remaining unchanged throughout. At status 1, P is then renewed (P = X – S), and its status is reset to 7. The same goes for the other settings. For a medium p^r setting, for example, agents only renew their perceptions every fourth tick, so the P status is set to 4, and advances from 4 down to 1 with each tick, remaining unchanged throughout, until it reaches status 1. Then it is renewed and the status reset to 4.

Note also that, technically, a value for X is reported for each cell across the field at each tick (X = *e*-*sk* x R (1)). This is necessary to generate S, and hence P, thereby ensuring agents can attend to unexploited opportunities. Of course, the reported X is only credited to performance as a payoff if an opportunity is actually selected or retained.

Initial commitment, c

The *c* slider influences continuity in the exploitation phase. Just as the uncertainty slider, U, influences an opportunity's eligibility for seizure, so the *c* slider setting captures an opportunity's eligibility for abandonment. Initial commitment to a newly seized opportunity ranges from one to seven ticks. Technically, just as P has a unique perception status where 1 signals its renewal, so *c* has a unique commitment status, where 1 signals an opportunity being freed up for abandonment. Until that point *c*, like P, remains frozen – neither abandonment nor perception renewal can take place. Hence, depending on the *c* setting, the agent continues to exploit the opportunity, regardless of any change in perceptions.

Agent execution skills, e-sk

Once an opportunity has been seized, the initial payoff depends on agent execution skills, *e-sk*, a fraction of one, tending towards 1 as the skill level increases. This is controlled using a slider with settings from low (20%) to high (100%). With R generated by a combination of chance guided by the *tfrc* settings, the payoff from a selected opportunity, X, is equal to the product of *e-sk* and R (1).

Agent surprise, S

As indicated, surprise, S, is the pathway from R to X for CTS-SIM. In rapidly changing, unpredictable environments it is observed to be 'assured and regular' (stylized fact 8). I therefore operationalize surprise, S, accordingly, using a random and bounded distribution.

Random models carry the advantage that nothing (within the range selected) can confound outcomes i.e. no factor can disturb the results (Gould, 2006). So there are equal probabilities of various levels of positive and negative surprise[65].

By interpreting surprise as 'mild astonishment', I place quantitative bounds on it (20 - 50%). This is discussed further in the next section.

Agent uncertainty, U

Agent uncertainty (for the 'organization' of agents as a whole) – the possibility that the organization might miss opportunities completely due to limited awareness – is captured using a slider. Just as the initial commitment slider above captures an opportunity's

[65] I do not associate environmental munificence with a bias toward positive S i.e. for CTS-SIM, although environments are for the most part munificent, there is not a greater probability of positive S than negative S, or vice-versa. Instead, I assume agents would adjust P for any such bias.

eligibility for abandonment, so the uncertainty slider influences an opportunity's eligibility for seizure.

Setting the uncertainty slider, U, to 80%, switches most of the turtles on to a state of awareness i.e. 80% have a perception of the opportunity on their respective patch. The other 20% of turtles have no perception of the opportunity on their respective patch, and so are unable to seize and exploit it. For all settings for uncertainty, U, below 100%, there is an excess of available opportunities. The U slider therefore assures the presence of opportunity superabundance. Agent uncertainty and superabundance therefore operate in unison.

Recall that in CTS-SIM performance, X, is the sum of all currently retained and exploited opportunity payoffs (Section 5.2.1). Also as indicated, the performance goal of strategy in the CTS context is growth. This is impacted by the chosen agent behaviours. High drive, *d*, can obviously be expected to positively impact growth. The CTS-SIM opportunity field, however, is limited in size. So it is necessary to calibrate the model such that growth can take place throughout each simulation run, without compromising on the other features of the system, in particular uncertainty and opportunity superabundance. Setting field size and controlling growth was a trial-and-error process (see Section 5.2.5).

5.2.3 Main assumptions

1) Irresistible, bounded and random surprise

A consideration when modelling surprise (stylized fact 8) is answering the call for its treatment as 'a variable with a threshold' based on its immanence in CTS systems (Perry, 1987; Eisenhardt and Sull, 2001; Cunha and Cunha, 2006). There are two questions: Is surprise avoidable? Is it quantifiable?

Regarding the first – the ability of agents in CTS systems to control and predict – I consider three alternatives:

a) *Surprise is avoidable*: it only occurs in the system when agents are slow to renew their perceptions i.e. is due to agent failure to keep abreast of changes in the system. Hence it is not a feature of the system but a condition of agent behaviour.
b) *Surprise is unavoidable, but can be resisted by agents*: surprise occurs throughout the system whether agents renew their perceptions regularly or not, but the two are inversely proportional.
c) *Surprise is irresistible*: surprise occurs throughout the system whether agents renew their perceptions regularly or not.

There is no evidence in the CTS literature reviewed to support alternative '*a*' above. Surprise and unpredictability are believed to be features of the system.

For alternative '*b*', agents are assumed capable of combating surprise by regularly renewing their perceptions. This is very different from agents *believing* themselves to be capable. Besides the unlikelihood of ever knowing all the inputs of a social system, a feature of CAS is its susceptibility to small changes in only one or two parameters of any one input. Locating small changes in highly dynamic environments can be likened to locating a moving needle in a haystack, placing severe constraints on the effectiveness of perceptions or their renewal.

Given the lack of evidence in favour of agent control (predictability) in both the CTS and CAS literature, I therefore assume alternative '*c*': surprise is irresistible (and therefore there is no special assumption that perception renewal reduces it). This follows CTS observations in favour of agent efforts to orchestrate and respond rather than predict and control.

Random, bounded surprise

As indicated, surprise, S, is the pathway via the exogenous environment, R, to performance, X, in the absence of sufficient evidence as to how decision-makers form perceptions, P. Also as indicated, a useful and robust approach to modelling a variable with a distribution that is not fully established is to adopt random modelling (Gould, 2006). The more challenging question for researchers, perhaps, is how to gather evidence of its quantitative effect.

Although there is a need for further study of this largely ignored variable in the CTS context (Cunha et al, 2006), it is possible to place bounds on surprise based on its meaning. Surprise can be understood as 'a sudden, unexpected discovery' and as 'mild astonishment'[66]. Therefore, if the perceived payoff from an opportunity were £8m, a payoff of £6m or £10m in the same period could be reasonably expected to induce surprise, being sudden, significant and unexpected. One might differentiate this response from that to a payoff of £2m or £20m, which is likely to extract a more strongly articulated response than that of 'mild astonishment'.

For these experiments I therefore limit the quantitative range of surprise to 20% - 50% of the exogenous potential, R. Fortunately ABMS is flexible enough to permit modelling of 'plausible' inputs and to allow for testing of their sensitivity to those inputs, which I also conduct.

[66] Surprise is understood to be 'a sudden, unexpected discovery' and as '*mild* astonishment' (Oxford English Dictionary, own emphasis).

2) Average skills assumption

Capturing the essentially heterogeneous and stochastic nature of perception skills was circumvented by using surprise, a unique experience for each agent. For the purposes of this research, the capture of heterogeneous managerial execution skills is possibly unnecessary. Abstraction in line with 'best practice', analogous to there being better or worse ways to hit golf balls or ski mogul fields, is possible (Eisenhardt and Martin, 2000). Nevertheless, it is within the remit of CTS-SIM to equip agents with unique, random execution skills. Hence, although I endow agents with an average skill level to begin with, the model is tested for its sensitivity to this assumption in Experiment #6.

3) Decision criterion assumption

Experiment #4 addresses the effects of the four chosen behaviours on overall performance. As indicated in Section 5.2.2, drive, *d*, is modelled as the probability that opportunities above a threshold value will be selected and persistence, *p*, as the probability that opportunities below a threshold value will be abandoned. Neither models the thresholds themselves.

However, doing so seems equally significant. Highly driven agents may, for example, select all positively perceived opportunities but only those above a high threshold, whereas less driven agents may select only half the positively perceived opportunities, but above a lower threshold. Both could result in similar numbers of opportunity seizures. So both criteria in this case, conviction (drive) and tolerance (threshold) ought to play a role in opportunism.

In Experiment #5, I therefore focus on the effects on performance of agents adopting different thresholds. I considered two decision-making alternatives, the first based simply on preference, the second on both value and preference:

a) *Best or worst*: agents select the *highest* perceived opportunity and abandon the *lowest*, repeating the procedure while guided by the settings for drive, *d*, and persistence, *p*.
b) *Above or below*: agents seize and abandon opportunities *above or below a particular threshold value*, repeating the procedure while guided by the settings for drive and persistence (beginning with highest or lowest).

Both decision-making alternatives were programmed. For alternative '*a*', the settings for drive and persistence govern the probability of *repeated* seizure and abandonment. The higher the setting, the more often the procedure is repeated. A difficulty with this alternative, however, is that the highest perceived opportunity value may be negative, yet result in selection, while the lowest value may be positive, yet result in abandonment. This seems unlikely i.e. that decision-makers will consistently seize opportunities with perceived negative payoffs and abandon those with perceived positive payoffs[67].

For this reason, I assume the perception *value* (rather than its preference rating alone) to play a key role in opportunity-transitioning. Hence, I adopt alternative '*b*', which accounts for perception values. This approach establishes a need to capture thresholds for seizure and abandonment (see Experiment #5).

4) Relative growth-of-attention assumption

From observation of simulation outcomes in the previous chapter, the CTS-SIM environment emerged as generally munificent, characterised by excess capacity, able to facilitate growth. However, with the introduction of agents and the integration of perceived and enacted environments into CTS-SIM the question of assuring environmental munificence resurfaces. A munificent exogenous environment might at some point fail to offer further excess capacity because of the limited size of the field, and due to growth of the organization or attention of the agents. As indicated in the previous section, therefore, a challenge was to estimate the model such that growth would be possible throughout each simulation run, and therefore not compromise on the availability of choices (stylized fact 12).

Theoretical growth constraints:

1) *Speed of growth*
   Growth in terms of the increase in the number and value of opportunities exploited is thus far influenced by agent behaviours. As indicated, in CTS-SIM agents representing the top level strategic executives may impose constraints on managerial freedom at the lower level, affecting the rate of growth. The implications of assumptions regarding agent freedom are considered and tested in the final batch of experiments.

Practical growth constraints:

1) *Growth limit*
   Overall CTS-SIM growth is limited by the size of the field, currently fixed at 400

[67] I consider this an assumption of the model nevertheless, since managers in their efforts to satisfice, may well on occasions misrepresent perceptions, motto: "We can't just sit back, we must try something!"

cells[68]. The implications of this artificial maximum are also considered and tested in the final batch of experiments.

2) *Speed of growth*

   This aspect of growth needed to be estimated such that the agent and system features described were not compromised. Trial-and-error search for a suitable rate for growth of agent attention was necessary i.e. a rate of growth in agent awareness able to 'keep the model up' without breaching other constraints. Three alternatives for programming the uncertainty slider, U, were considered:

   a) *Absolute, fixed growth:* the number of patches added to the agents' field of attention over time is fixed and depends on the U slider's parameter setting.
   b) *Relative, variable growth:* the number of patches added to the agents' field of attention over time depends on the current field of attention.
   c) *Hybrid growth*: agents' field of attention expands through a combination of 'a' and 'b'.

The notion that agents increase their field of attention in line with their ongoing performance (i.e. their current size or status, alternative 'b'), rather than endowing them with the goal and ability to increase their field of attention at a fixed, preset rate was adopted. I leave further investigation of the latter to future research.

5) Simplification: minimal payoff delays

There are two types of delay relevant to the process modelled in CTS-SIM, one between perception formation and action, the other between action and payoff. The first is modelled as perception renewal, p^r (previous section), the second prompts an assumption about delays in payoffs.

Agents form perceptions, P, and act on them to generate payoffs, X, but the latter may accrue in the same period or some later period[69]. I consider three alternatives:

1) no delays (payoffs accrue immediately);
2) minimal delays (high probability of a 'short' delay, low probability of a 'long' delay);

[68] An obvious practical consideration was the time taken to run simulations. Increasing the size of the field from 400 cells to 2500 in the final batch of experiments slowed simulations more than tenfold.

[69] Other inertial forces that in practice might affect the intentions/action process, that undermine agent control of change, are deemed to affect agent willingness/ability to act and are therefore abstracted into behaviours (dpp^rc) and skills (*e-sk*) for the purposes of this research.

3) maximal delays (high probability of a ‘long’ delay, low probability of a ‘short’ delay).

For ‘no delay’ accrual is immediate (100% in the current period: tick 1); for ‘minimal delay’ accrual is spread over the next two ticks with a high probability (80%) and over the next three ticks with a low probability (20%); for ‘maximal delay’ it is the reverse i.e. there is a higher probability of longer delays:

		Tick		
	Probability	1	2	3
no delay	100%	100%	-	-
minimal delay	80%	50%	50%	-
	20%	0%	50%	50%
maximal delay	80%	0%	50%	50%
	20%	50%	50%	-

Table 5.1. Payoffs as a % of X

Given that I focus this research on simulating successful organizations operating in highly dynamic environments, I follow the direction of the CTS literature by assuming that they are unable to avoid delays altogether, but nevertheless able to minimise them. I test the implications of the ‘minimum delay’ assumption in the final batch of experiments.

5.2.4 Processes

The flowchart below (Fig. 5.6) is a simple but useful aid to understanding the CTS-SIM process. It begins with agents facing a choice of opportunities (controllable by the U slider). Selection is only possible if the agent is attentive and the opportunity is perceived to meet requirements. The selection process is repeated with some probability in line with agent drive, *d.* A selected opportunity is retained in line with agent initial commitment, *c*, and persistence, *p*, otherwise it is abandoned. At each tick, overall agent uncertainty, U, is updated in line with the relative, variable growth-of-attention assumption.

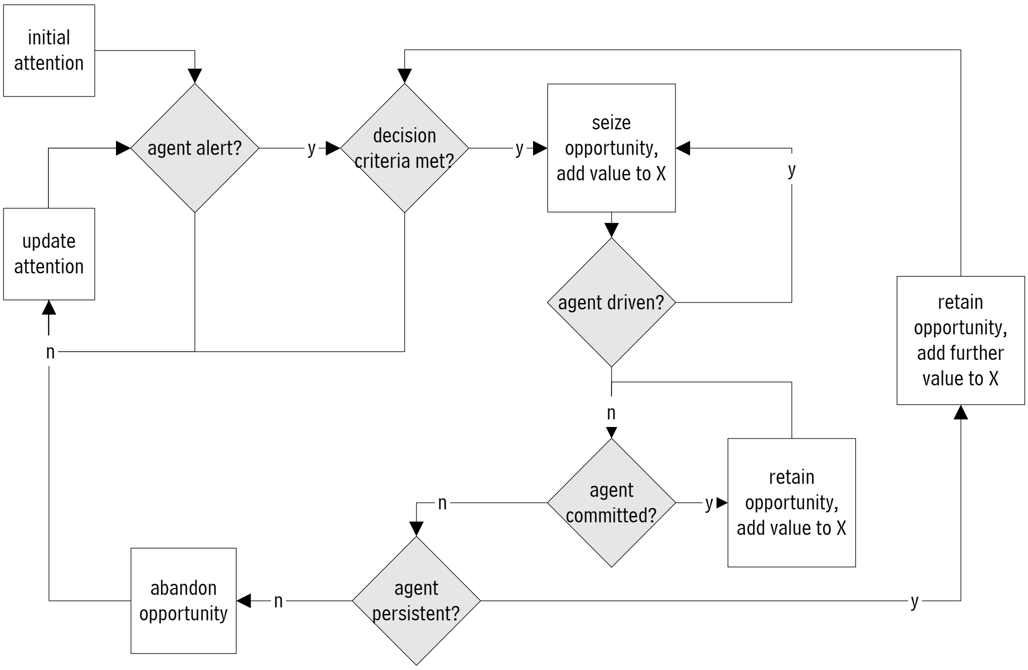
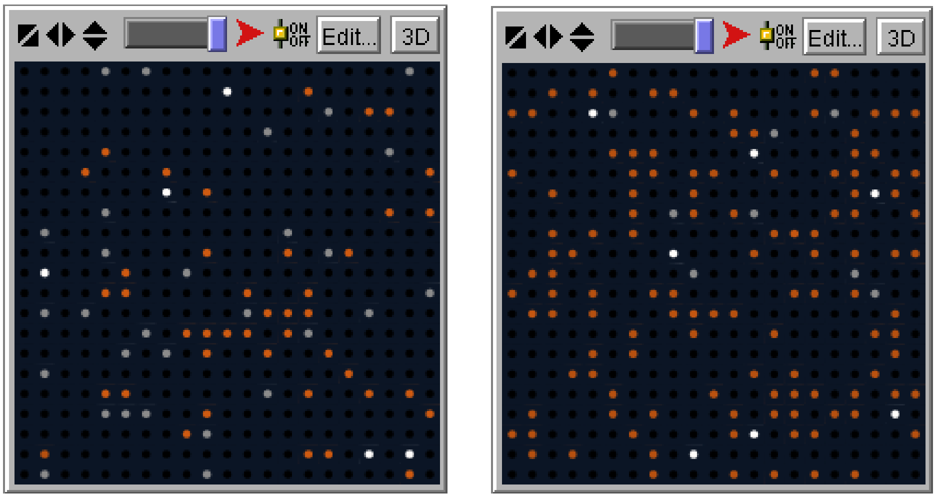


Fig. 5.6. CTS-SIM agent behaviours, $dpp^r c$, and performance, X

Fig. 5.6 is not only useful for underscoring the interdependence of the micro-level behavioural variables, $dpp^r c$, but also for identifying the micro-macro feedbacks in the environment. For example, whereas the probability of agent initial commitment is shaped by the *c* setting, so too is the performance of the group or organization of agents, X. This aggregate performance influences the level of exploitation (the probability that new opportunities will be seized) and hence the number of opportunities in the initial commitment phase, at the next tick. Such micro-macro feedback loops exist between each of the agent behaviours and the organization.

Ascribing different colours to cells depending on their states, and observing the grid and graphs during runs, are further useful ways of understanding how the model works. Patch agents and turtle agents change colour with some probability depending on the respective mix of chance and constraint. Fig 5.7 below shows the CTS-SIM topology at a point in time:

- patches outside agents' attention are black
- patches newly attended-to change from black to grey
- new selections change from grey to white
- retentions turn white to orange
- abandonments orange to pink, thereafter to black or to grey



a) *b)*

○ newly seized ● abandoned ● retained ● attended-to (unselected) ● unattended

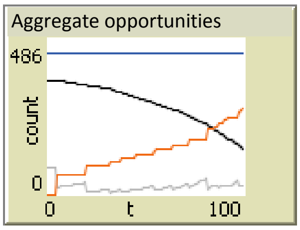
Fig. 5.7. Opportunity field showing agent transitioning at a point in time

So the grid in action is a way of representing ‘the organization of agents responding to rapid change by ceaselessly recombining its portfolio of business units, thereby generating novelty whilst retaining the best performers.’

Note that the black area is that part of the exogenous CTS-SIM environment which is unknown, the rest of the field (white, pink, orange and grey) is the perceived CTS-SIM environment, part of which is the exploited CTS-SIM environment (orange).

The graph below (Fig. 5.8) is also useful, tracking changes in the *numbers* of turtles during a simulation:

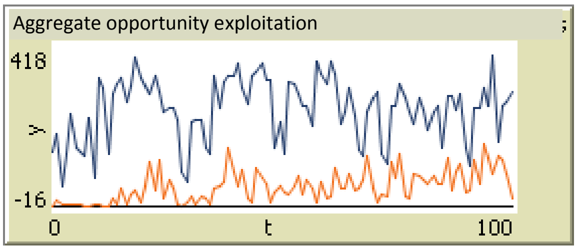
1) *Blue curve*: fixed overall number of opportunities available on the grid, hence a straight line.
2) *Orange curve*: increase in the number of opportunities retained over time, hence a curve with positive slope.
3) *Grey curve*: agent attention based on the relative growth-of-attention assumption
4) *Black curve*: agent uncertainty, which decreases with the increase in exploitation, but which never reaches zero since the model is estimated to ensure this (Section 5.2.2).



— potential (R) — retained (X) — newly attended — unattended

Fig. 5.8. Graphs showing aggregate *opportunity counts*

It is also helpful to note how agents can be seen to attempt to align with the exogenous environment. In Fig. 5.9 the blue curves track the total *value* of opportunities on the grid, R, while the orange curves track the payoffs from seized and retained opportunities, X.



tfrc: hhhh

— potential (R) — exploited (X)

Fig. 5.9. Graphs showing aggregate *opportunity values*

In sum, the richly connected, turbulent field of opportunities constructed in the previous chapter is now populated by decision-making agents. The program is able to generate values for the exogenous environment, R, and for agent surprise, S, crediting the agents with payoffs, X. It only does this if the agents are aware of the opportunity in the first place, and only if the opportunity qualifies after being compared with the perceptions of the other agents, as one would expect in CTS systems.

Payoffs can be positive or negative and depend on the level of execution skills. Agents can influence opportunity-transitioning through their behaviours. Furthermore, the p^r setting controls the status of agent perceptions. The outcome: unique values for R, X and P change synchronously on each cell at each tick. Simulations can now be run without the need to compromise on the most important features of CTS systems.

Before progressing to the experimentation stage, it is useful to briefly consider the nature of the CTS-SIM agents and some important abstractions.

CTS-SIM agents and abstractions

The agent variables and attributes chosen in this chapter were arrived at in the same three-stage process as that adopted for the CTS-SIM environment. I began with the isolation and development of alternative, ‘possible’ variables on a ‘clean sheet of paper’, exploring the literature for previously used relevant variables, then choosing those I considered most appropriate for the task.

Although CTS-SIM agents should behave like opportunists, they need only be as intelligent (proactive, reactive and social) as required for the experiments conducted i.e. relatively intelligent (relative to the goals of the research). In the CTS-SIM environment, of course, neither intelligence nor opportunism is enough to protect the agent from surprise or error. As Thompson (1967) and Porter (1995) suggest, there are attempts to continually realign with the environment through goals and actions at all levels, only without any guarantee of success.

It is natural to represent decision-makers through autonomous, heterogeneous agents (North and Macal, 2007). The decision-making agents (turtles) in CTS-SIM each have their own identity and are situated on the environmental patches. However, a turtle does not need to perceive what is around it (neighbouring turtles do that), only what is below it, on its own patch. Their ‘intelligence’ is captured in the form of a capability of following the changes that take place on their patches, hindered by the element of surprise. *So, rather than plan and predict, turtles perceive and respond to changes on the opportunity patches.*

For CTS-SIM then, it does not make any difference where, in relation to one another, a turtle is situated on the grid. Nor does it need to be mobile. For this version of CTS-SIM at least, it was possible to ignore spatial interactions, even though the toolkit is geared toward such a facility. This version is just a more simple and suitable way of modelling the problem[70].

Further, whereas turtles are identifiable, self-contained and heterogeneous, and can behave actively and autonomously, not all of them have an idea of what is on their patches. Those inside the organization’s ‘field of attention’ do, those outside do not. To resolve the fact that some turtles are ‘active’ and others are not, it is necessary to take a reasonably flexible view of who a turtle represents. A manager responsible for deciding and acting on a single opportunity is represented by a single ‘active’ turtle, and a manager responsible for

[70] As indicated in Chapter 3, some authors might class this version of CTS-SIM as a conventional proto agent-based simulation, being too abstract to qualify as an ABM. This would be because there are no rules to change the rules, because turtles do not distinguish each other’s traits, or because boundaries between them are flexible.

many opportunities is represented by just as many ‘active’ turtles. Opportunities outside a manager’s attention are represented by inactive turtles, one for every patch.

So the single ‘organization’ on the CTS-SIM grid can be understood to consist of one or more decision-makers, represented by any number of active and inactive turtles. The organization is a ‘flexible constitution of agents’. This is a useful way of representing their sub-rational, ‘satisficing’ human counterparts. As their attention to the field of opportunities changes over time, so does their ability to form perceptions and act. As such they too *orchestrate* their environments.

The model plays down the role of learning, negotiating, forming and dissolving relationships that inform the process of perception formation. The starting point is one at which the individual perceptions of the turtles have been formed (Fig. 2.1). This abstraction is useful, because capture of the entire process can be elusive and complicated but, more importantly, is unnecessary for the purpose of this research.

Once perceptions are formed, these are compared with a simple exchange of information. This happens at each tick. To represent an organization in which leaders bring the inputs (perceptions) ‘to the table’, it is necessary to relegate their subordinates to the background and to view turtles as representing leadership[71]. Either way, there is no collective optimization of agent behavior – that is, the model abstracts away from the cognitive processes that shape behavioural alteration[72].

In the model, the observer agent can control what happens ‘at the table’. It cannot itself perceive opportunities or act on them, but it can lift or impose constraints on the overall number of opportunities seized and abandoned. This is an abstract way of representing the leadership of the organization. In practice, leadership might ‘request’ the input of the decision-makers, compare their inputs according to a set of criteria, and then permit or prohibit them to select or abandon. Leadership might give the decision-makers the go-ahead in advance, without requesting or comparing their inputs, but provide instructions for action within certain constraints.

In Experiment #6, the model is extended to enable the user to control or disable the authority of the observer. Turtles act in line with the degree of freedom granted by the observer, so when the authority of the observer is disabled, the turtles are left to their own devices and simply act on their perceptions. Endowing turtles with autonomous perceptions

[71] To the extent that individual strategies are expressed by turtle perceptions, which are partly random, CTS-SIM captures a feature of CAS which evolutionary game theory models (with actors that implement a single strategy) do not.

[72] An interesting model extension would be to investigate outcomes when agents are programmed to alter their behaviours/thresholds on the basis of previous successes/failures. This version of CTS-SIM does not account for this.

while also being able to constrain their decision-making, is an original feature of the model that sets it apart from other models, even from other agent-based models of organizational behaviour.

5.2.5 Verification

As in the previous chapter, I take steps here to verify the operational efficacy of the model i.e. to ensure that the model contains no errors, oversights or bugs (North and Macal, 2007).

Monitoring and debugging

Again use was made of the syntax checking, command centre, runtime error reporter and speed adjustment facilities in NetLogo to trap any coding errors. The model reports a runtime error when there is a bug in the code and when certain constraints are breached, a means of verifying that the system attributes are maintained throughout. Use of the agent monitor and commander tools to track changes in the status of a chosen agent was intensified, given the growing list of specifications for each patch and turtle[73]. Again, simply slowing or stopping simulations for inspection, and supplementing the use of monitors with graphs in order to track changes, proved useful as further techniques to ensure CTS-SIM works as intended.

Sensitivity testing

As in Chapter 4, sensitivity testing continued to play a central role in the modelling process. In particular, the need to run many simulations revealed susceptibility of model outcomes to small sample sizes yet robustness to cross-sectional observation i.e. for the stated purposes.

The findings of the sample size, run length and scope of application tests that follow were important to assure the robustness of the experimental outcomes. The sensitivity and assumption testing in the preliminary experiments and in Experiments #5 and #6 had the common objective of ensuring that the simplifications of CTS-SIM do not seriously detract from the credibility of the model or its ability to provide important insights (Carley, 1996).

[73] Each patch agent has a unique specification: coordinates, values (for transience, frequency etc.), colour, label and label colour. Each turtle has in addition: type, shape, breed, and values (for p^r status, P, X, S etc.)

Sensitivity testing was also important to develop an understanding of the sensitivity of overall performance to changes in agent behaviours and different strategic orientations.

Thereafter, testing the effects on R of the underlying assumptions (surprise, average skills, and payoff delays) was required in order to demonstrate that none of these simplifications seriously detracts from the credibility of simulation outcomes.

Parameter sweeping

Again the NetLogo facility, BehaviorSpace, simplified the experimental phase (Fig. 4.25). It enables model authors to define commands, conditions for stopping simulations, to fix parameter settings, define the reporter, to stipulate run lengths etc. During experimental runs, CTS-SIM can also be watched in a window. All runs were logged[74] and outcomes exported for analysis. This was followed when appropriate by amendments and further runs, until the desired data were available.

The systematic variation of model parameters made it more convenient to experiment with a larger number of variables than would have been the case with the same research constraints using other methods. It also facilitated a wider and more thorough search of the relevant state-space. The large amounts of data generated due to the uncertainty built into the model, were exported without restriction due to the virtually unlimited number of rows and columns available in Excel 2007.

These facilities, BehaviorSpace in combination with Excel 2007, for the reasons outlined in the previous chapter, make one-stop modelling at this level possible. CAS generally require a wide search and analysis of the relevant state-space, and the very large amount of data generated under the conditions described renders traditional methods impractical for the most part.

Having verified the individual effects of *tfrc* on R and the heterogeneity of R in the previous chapter, verification of the following key features of CTS-type systems is required, to ensure the extended model works as intended:

1) Surprise and error are pervasive in CTS systems due to the inability of decision-makers to accurately perceive and predict the future and due to their skills or resource limitations, so the model should confirm this (stylized fact 8).

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[74] NetLogo treats experimental setups as part of the model, and therefore all experiments were named and saved within each updated version of CTS-SIM. BehaviorSpace experiments are saved in a plain-text data format, a '.csv' file, readable by text editors and most spreadsheet and database programs.

2) A limitation of decision-makers is their uncertainty due to attention limits, so CTS-SIM should assure agents are unable to attend to all available opportunities in the exogenous environment (stylized fact 8).
3) Organizations operating in open, social contexts are characterized by large numbers of interdependent stochastic decision-making elements, so the model should assure that there are many, active[75] agents whose behaviours are interdependent and that produce nondeterministic outcomes (stylized fact 9).
4) CTS systems are CAS with many interacting components that possess some level of freedom and autonomy, so the model should confirm that agent decision-making is autonomous within organizational constraints, and it should assure their individuality through heterogeneous perceptions, P, and performance, X (stylized fact 10).
5) The driving force of dynamic market processes are the profit-oriented, decision-makers, so simulations need to show agents that represent driven individuals shifting flexibly among novel opportunities in pursuit of opportunity-based payoffs (stylized fact 11).
6) To be consistent with observed management practice, CTS-SIM should also confirm that performance outcomes are the result of external drivers, internal efforts and pure chance – able to emerge due to the stochastic, probabilistic model construction (stylized fact 13).
7) Whereas the above propositions address an endogenous environment shaped by the agents, the ground itself is always in motion, so CTS-SIM should blur the distinction between organization and environment and be able to demonstrate that changes in R can affect perceptions, P, and performance, X (stylized fact 14).
8) CTS-SIM should assure that the phenomenon of excessive market opportunities – due to technological change, globalization, lower barriers to entry etc. – is captured through large numbers of available opportunities beyond the perceptive and exploitative capabilities of the organization as a whole (stylized fact 12).

The five verification tests that follow serve to confirm that the model is programmed correctly and that it captures each of the above features. In the graphs that follow, agent perception and exploitation are shown on a single patch in an environment with low *tfrc* settings. The graphs track the values of R (blue curve), P (grey curve) and X (orange bars)

[75] Agents are not mobile on the grid, but they are active in the sense that they form and act on perceptions.

throughout each simulation, henceforth referred to as RPX graphs (environment-perception-performance).

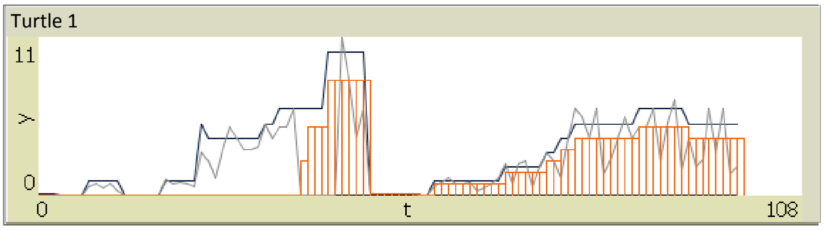
Externally driven, perceived and exploited opportunity values, y (*y*-axis), are shown as they unfold over time, t (*x*-axis), for an arbitrary opportunity sequence. Patch agents represent the R values generated on each patch (previous chapter). Each patch is now populated with its own decision-making agent (turtle). The uncertainty slider ensures that not all turtles are 'switched on' i.e. during simulations turtles cannot attend to all opportunities on the field simultaneously. Their field of attention, as a group or organization may increase or decrease as time unfolds. The model is estimated so that the turtles' field of attention and opportunity exploitation can grow over time.

On patches with turtles that are 'switched on', each turtle is endowed with a perception of R (via S). Their perceptions of their respective opportunities are compared at each tick as a basis for selection or abandonment. As one would expect, the best perceived opportunities, or those perceived to be sufficiently attractive, are seized and the worst perceived, or those failing the agreed criteria, are abandoned. Whether an opportunity is seized or abandoned by a turtle on a patch depends: 1) on the respective perceptions of all the other turtles and, 2) on the constraints imposed by the observer (leadership)

1) Assurance of agent interdependence

In Fig. 5.10 below the agent attends to the opportunity throughout the simulation (grey curve) only exploiting it from about the 40th tick onward (orange bars). Although the agent (turtle number 1) perceives the opportunity as attractive, it is not initially selected because it fails to qualify over the other turtles' perceptions. The contribution of each turtle to the performance of the organization therefore depends on the perceptions and contributions of the other turtles. The performance of the organization is measured as the aggregate of all the exploited opportunities at a point in time, and over time.

tfrc: *llll*



— potential (R) — perceived (P) — retained (X)

Fig. 5.10. Perceived and temporarily exploited opportunity

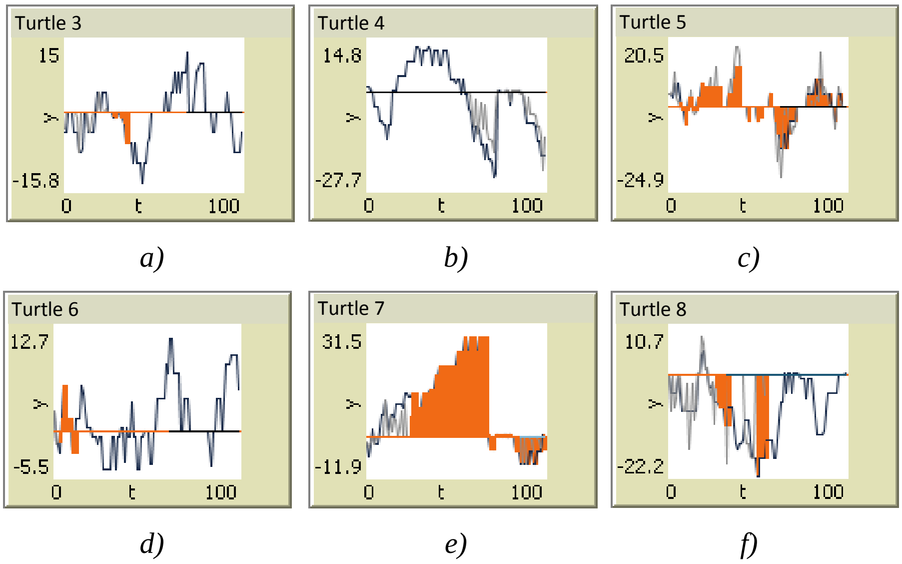
2) Assurance of agent uncertainty, heterogeneity, surprise and error

The RPX graphs below show perception and exploitation of six different agents in a more *dynamic environment (tfrc*: *lhm$^+$m)*. They serve to confirm the individuality of agent perceptions, P, and of agent performance, X. This is demonstrated by the unique P trajectories (grey curves) and payoffs, X (orange bars). Note that payoffs can be positive (upward orange bars) or negative (downward bars).

Throughout the simulations there is evidence of agent decision-making error (negative payoffs and missed payoffs), agents being unable to predict R. This is evidenced by both premature and belated seizures and abandonments.

Turtles 3-8

tfrc: *lhm$^+$m*



— potential (R) — perceived (P) — retained (X)

Fig. 5.11. Agent autonomy and heterogeneity

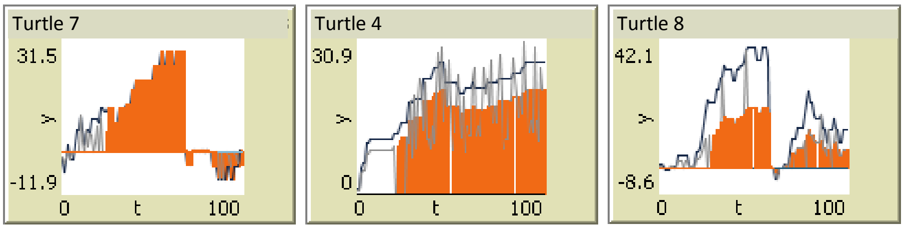
Note also that positive P alone does not assure selection, just as negative P alone does not assure abandonment. Agent decision-making depends on the decision criteria and comparison among alternatives. Evidence of this can be seen in graph *e*, for example, where there is no initial opportunity selection (although P is positive) nor abandonment near the end of the simulation run (although P is negative).

The above graphs also demonstrate limited attention to opportunities, graph *e* being the only case of full agent attention throughout the simulation i.e. the only graph with a P curve or exploitation throughout.

3) Confirmation that performance depends on agent skills

In each of the above graphs (Fig. 5.11) the *e-sk* setting is 100%, hence X = R when an opportunity is selected.

Figs. 5.12*b* and *c* below show the functionality of other *e-sk* settings[76].



a) e-sk 100% *b) e-sk 80%* *c) e-sk 50%*

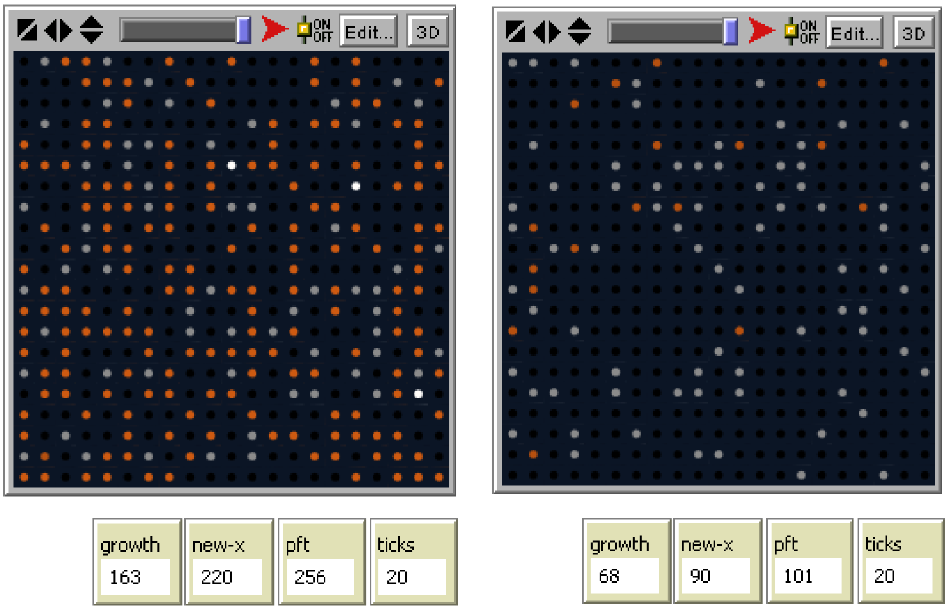
Fig. 5.12. R, P and X at different *e-sk* settings

4) Verification tests of limited agent attention, flexible shifting among opportunities and opportunity superabundance

Increased uncertainty in an environment should, *ceteris paribus*, be accompanied by lower growth, agents not attending to the same scope of opportunities. Fig. 5.13 below confirms this. At higher uncertainty (Fig. 5.13*b*) recorded growth and seizures are lower (note growth and new-x monitors).

[76] Note that *e-sk* settings have the same effect on X for positive and negative R.

U parameter setting: *50%*, U parameter setting: *80%*,



(a) *(b)*

Fig. 5.13. Opportunity field showing agent transitioning at a point in time

Limited agent attention is also evident in Fig. 5.14 below. Here the agent only attends to the opportunity temporarily, very late in the simulation. The numerous grey curves show P for all p^r settings.

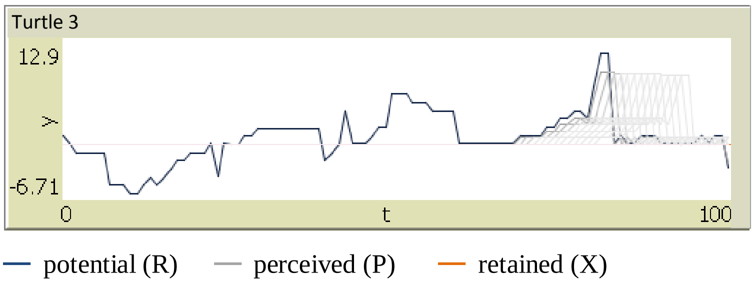
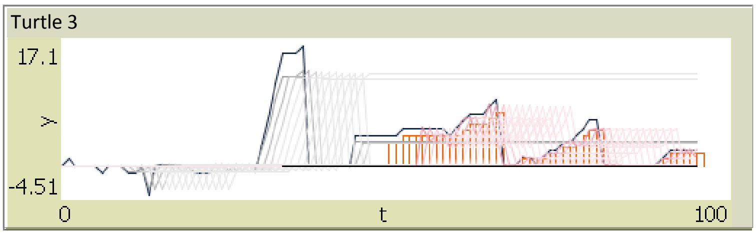


Fig. 5.14. Unexploited opportunity temporarily perceived

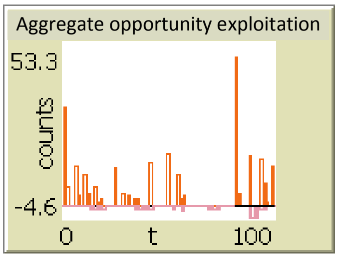
In Fig. 5.15 the agent begins to attend to the opportunity earlier in the simulation, actually selecting it about half way through (orange bars).



— potential (R) — perceived (P) — retained (X)

Fig. 5.15. Perceived opportunity temporarily exploited

The bar graph below serves as a form of verification of the instability of the modelled system, with irregular seizures (upward orange bars) and abandonments (downward pink bars). It also serves as a form of verification that growth takes place, seizures exceeding abandonments.



seizures abandonments

Fig. 5.16. Counts of opportunity seizures and abandonments

5) Verification test for environmental influence on agent perceptions and performance

As indicated, turtle perceptions should be shaped by the environment: P = X $\pm$ S (2), where X depends on R. Confirmation that agents attempt to align with the environment during opportunity exploitation, supported earlier at the aggregate level in Fig. 5.9, is also supported at the individual level below. More disrupted exploitation (through more frequent seizures and abandonments of opportunities of shorter duration) is evident in more dynamic, disrupted environments i.e. exploitation is more disrupted in graphs *a*, *b* and *c* than in graphs *d*, *e* and *f*.

Turtles 3-8 (randomly selected opportunity sequences)

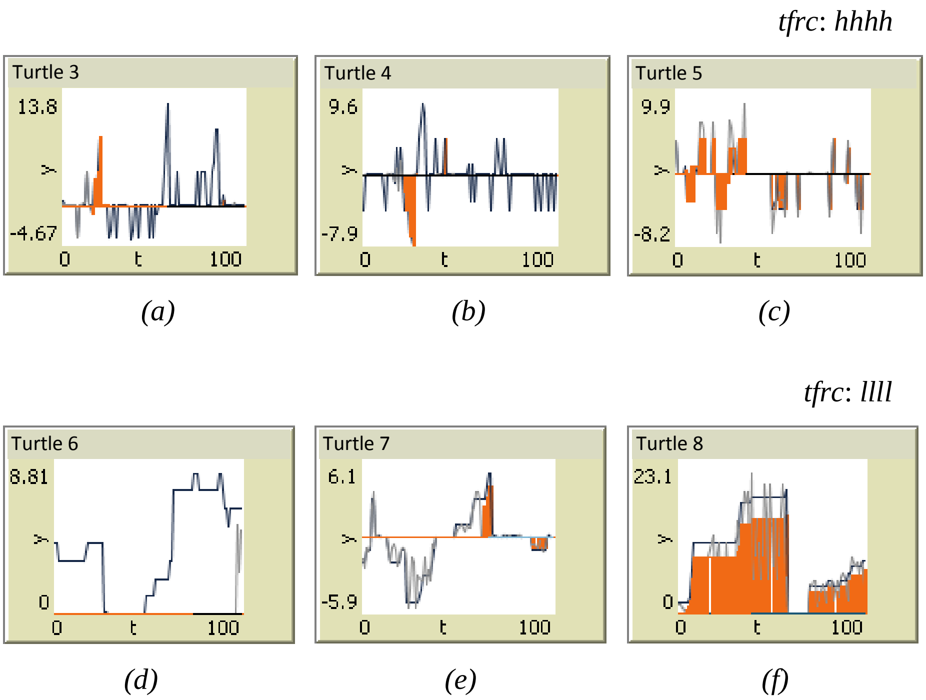


Fig. 5.17. R, P and X in different environments

The above simulation outputs also serve as theoretical support for the observation that under conditions of low munificence, organizations can still prosper e.g. in Fig. 5.17 graphs *a* and *e*, agents receive net positive payoffs. In these examples CTS-SIM agents are more restricted in their choices. The effect, over time, is reflected in the fewer opportunities they exploit and lower accumulated payoffs. Hence, they are more dependent on the choices they make, and more vulnerable than otherwise. Performance is likely, though not certain, to improve in more munificent situations (graphs *d* and *f* above). Baum and Wally write (2003, p. 1111): “Environments with low munificence reduce strategic decision-makers’ degrees of freedom. Indeed, researchers point to heightened risks of failure when firms have few resources because some options cannot be afforded: thus, the importance of the ‘right’ choice is raised (Slevin and Covin, 1995). However, some firms... may survive in low munificence environments. The general effect is that munificence enhances firm performance.”

In sum, the above tests confirm agent autonomy and heterogeneity. They also confirm that agents do not attend to all the available opportunities. There is also visible evidence of temporary exploitation due to agent interdependence. The model also accounts for the role of agent skills. Although the grid shown in Fig. 5.13 is a static representation of the model at work, it serves to corroborate the evidence shown in the graphs. In particular, it confirms the presence of superabundant opportunities and shows how agents shift flexibly among opportunities. To be consistent with management practice, the model also confirms that performance outcomes are the result of external drivers, internal efforts and sometimes pure chance.

Each of these tests contributes to the overall likelihood that the theoretical logic and computational representation of the model are correct.

5.3 Experimentation

I now progress to the empirical, normative and heuristic goals of the second batch of experiments:

- Experiment #4: Exploration and testing of the effects on aggregate performance of agent behaviours, by varying the parameter settings.
- Experiment #5: Exploration and testing of the effects on aggregate performance of agent decision-making criteria, by adding further detail to CTS and varying the parameter settings.
- Experiment #6: Exploration and testing of the effects on aggregate performance of model extensions (i.e. heterogeneous agent skills, agent decision-making freedom) by adding further detail to CTS-SIM and varying the underlying assumptions.

Presentation, descriptive statistics

In the previous chapter, I made use of graphs generated by NetLogo as a tool for the dynamic representation of the exogenous environment (R trajectories). In this section, I use both graphs and box plots to observe and analyse agent behaviours and performance. Although there are other ways of presenting simulation results (e.g. as probability functions), box plots have descriptive strengths that are appropriate when the focus is on the behaviour of the elements of the model[77]. The box plots offer only a static perspective of outcomes, but they are useful for descriptive statistical analysis of CTS-SIM outcomes over time. For an idea of the statistical dispersion of the data generated by CTS-SIM, it is possible to observe patterns within the entire sample, and therefore, in contrast to other methods of strategic

[77] Stafford, http://dl.getdropbox.com/u/306562/stafford123.pdf.

management research, to observe and analyse minimum and maximum data observations and also the more meaningful inter-quartile range, and to show central tendencies.

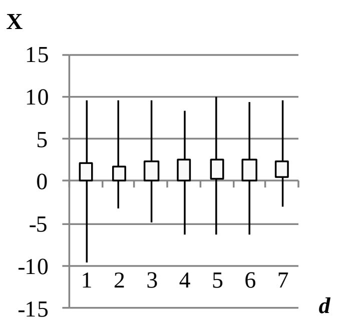
In the previous chapter a single simulation run or a few runs were sufficient, since only 'narratives' were required. In this chapter, I first varied the number and the length of simulations to test for sufficiency in generating likely emergent behaviours. The expectation was that many simulation runs would be required to produce a meaningful result, outputs being likely to vary with small samples (Richiardi et al, 2006).

I ran three preliminary tests with the following aims: 1) *Sample size*: to demonstrate the effect of changes in agent drive, *d*, on performance, X, based on different numbers of simulation runs, 2) *Length of observation*: to demonstrate the effect of changes in drive on performance based on different lengths of simulation runs, 3) *Scope of application*: to demonstrate the effect of changes in drive on performance based on observations at different stages of simulations. These simulations are run under high settings for environmental dynamism, *tfrc: hhhh.*

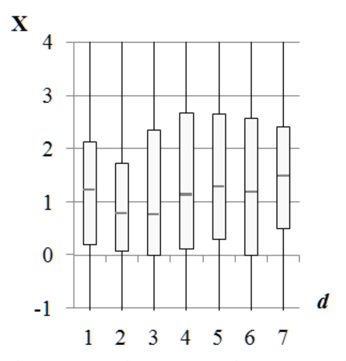
1) Sample size test

For the sample size test, I vary the number of simulation runs to determine how many are necessary to demonstrate any relationship between drive and performance. The box plots below (Fig. 5.18) show the need for larger sample sizes: plots *a* and *b* show no discernable pattern after 30 runs of length 30 ticks, whereas plots *c* and *d* show a clear pattern after 200 runs of even shorter length, 12 ticks.

This is easier to see in the box plots on the right (Fig. 5.18*b* and *d*), which ignore the minimum and maximum observations[78].

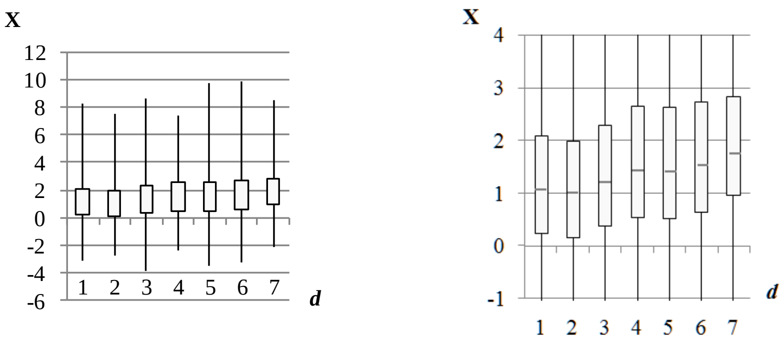


a) Runs 30, length 30 (ticks)



b) Runs 30, length 30

[78] Given the lack of pattern among all minimum and maximum observations in these tests, they are not shown further.



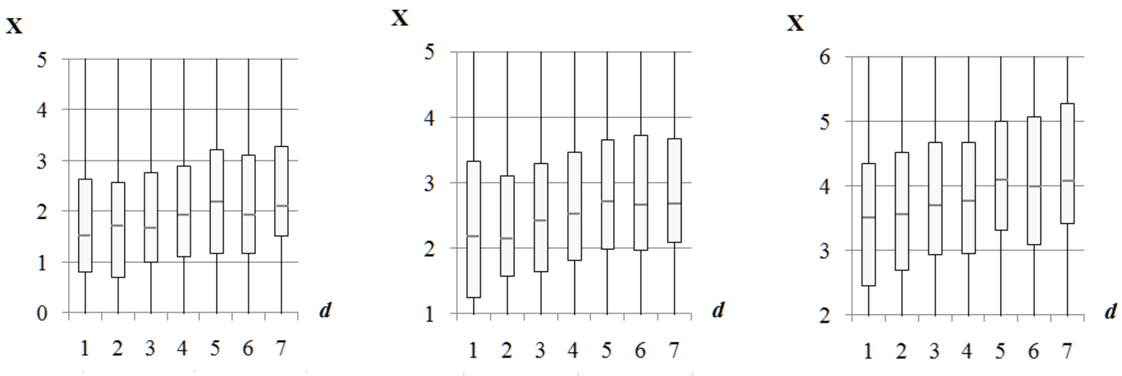
c) Runs 200, length 12

d) Runs 200, length 12

Fig. 5.18. Number of runs required for pattern observation between *d* and X

<u>*2) Length of observation test*</u>

For the 'length of observation' test, I ask whether cross-sectional observation is capable of demonstrating a relationship between drive and performance. Having established that a positive relationship between drive and performance could be observed after just 12 ticks, I show results of outcomes at a point in time by stopping the simulation. The results shown below are based on a large sample size (200 simulations).



a) 30th tick

b) 50th tick

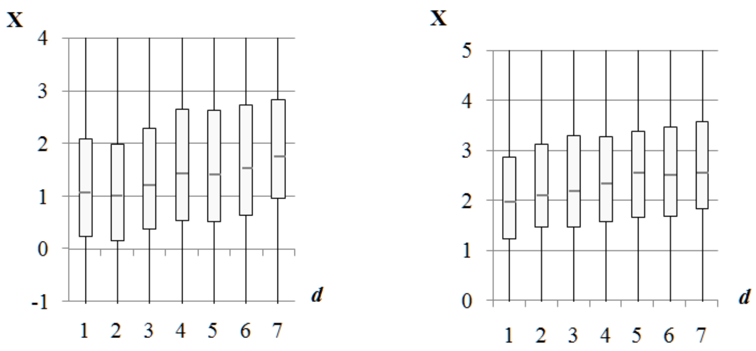
c) 100th tick

Fig. 5.19. Cross-sectional observations
(sample size 200 runs)

<u>*3) Scope of application test*</u>

Having established the importance of large sample sizes and the usefulness of cross-sectional observation given large sample sizes, I test if this applies at any time during simulation. In other words, does a sample size of 200 runs reveal a relationship between *d* and X at an early phase of the simulation (i.e. ticks 12 - 24) or only after the simulation has been run longer (i.e. ticks 84 - 96)?

Fig. 5.20*a* and *b* below reveal a relationship in each case. This shows robustness to initial conditions, and applies to situations in which only a few opportunities are being exploited as well as to those where the exploitation of opportunities takes place on a larger scale e.g. after some growth has taken place.



a) Ticks 12 - 24 *b) Ticks 84 - 96*

Fig. 5.20. Early and late phase observations
(sample size 200 runs)

Facit: The sample size test shows the susceptibility to error of inferences made from small sample sizes for this research; the run length test shows the potential for meaningful cross-sectional observations from larger sample sizes; and the scope test shows that the simulation outcomes can be useful to organizations exploiting few or many opportunities, before and after some growth has taken place.

With a reasonable understanding of CTS-SIM at this point, it is possible to proceed the main phase of experimentation.

5.3.1 Experiment #4: *Examining the relationships between opportunity-based agent behaviours and organizational performance*

Aim:

To test the effects on performance of each of the four agent behaviours (drive and persistence, perception renewal and initial commitment, dpp^rc) in more dynamic environments. I compare agent performance outcomes in three different environments, E1 (*tfrc: hhhh*), E2 (*tfrc:* $lhm^{+}m$) and E3 (*tfrc: llll*)[79].

The expectation is that increased drive and initial commitment should positively impact performance. It is unclear however, whether they will do so more strongly in E1 than E3.

It is also unclear whether persistence will have a positive impact on performance in more dynamic environments, given the lack of attention to the effect on performance of opportunity abandonment in the literature. It is also unclear what impact the renewal of perceptions will have on performance, given the assumption of unavoidable and irresistible surprise.

Here is potential for useful new insights for CTS. Unless otherwise stated, minimum sample size was 100 runs per setting, and minimum run length 100 ticks.

Settings[80]

Experiment #1	Variables				Sample		Reporter
	d	*p*	p^r	*c*	*runs*	*ticks*	
E1 (*tfrc = hhhh*)							
E2 (*tfrc =* $lhm^{+}m$)	*1-7*	*1-7*	*1-13*	*1-13*	*100*	*100*	X (aggregate)
E3 (*tfrc = llll*)							

Table 5.2. Settings for Experiment #4

Outcomes, observations

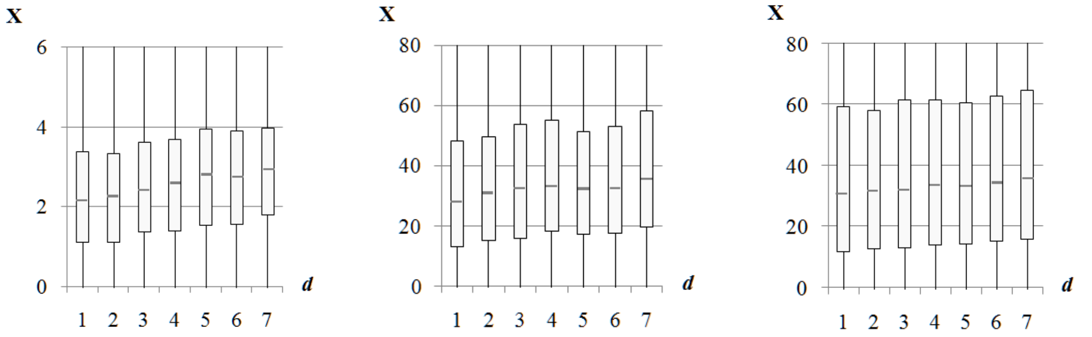
<u>#4.1. *Relationship between drive, d, and performance,* X</u>

The box plots below show the effect on performance, X, of varying agent drive, *d*, under varied conditions of environmental dynamism, with the other agent behaviours fixed. Levels of surprise and uncertainty are high.

Drive, *d*, has a positive effect on performance, X, most significantly in E1 (*tfrc = hhhh*). The causal relationship between *d* and X in E2 across the range tested, appears to be unstable. In E3 it is more moderate but stable.

[79] Again, experiments are based on flow assumption 2 (see Section 4.2.3).

[80] Patterns from simulation results at range settings 80/20 were not different from those at 95/5 (refer Section 4.2.2), so all results shown here are at the 80/20 range.



a) E1 (tfrc: hhhh) *b) E2 (tfrc: lhm⁺m)* *c) E3 (tfrc: llll)*

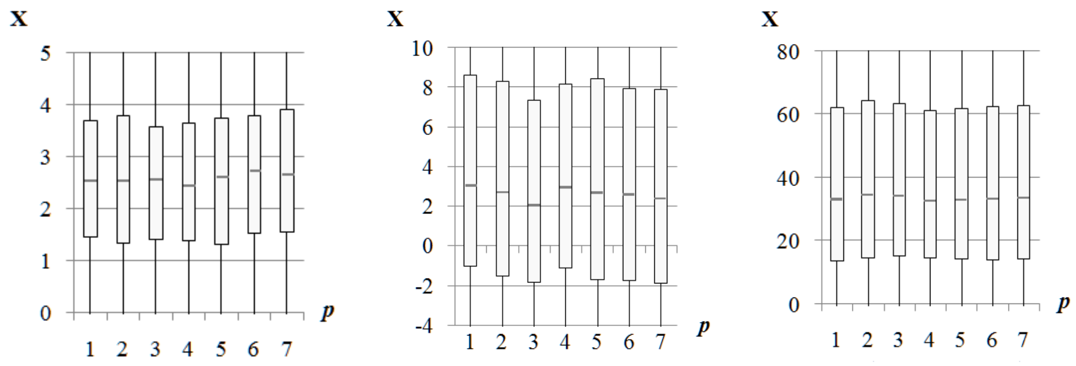
Fig. 5.21. Effects of *d* on X in different environments
(Runs 200; Length 100 ticks)

Note the values on the *y*-axes above. An increase in drive, *d*, across the range of settings (*low* to *high*) barely increases median performance, X, in E1 (increase from 2.1. to 2.9). Increases in median performance across the range of *d* settings in E2 (roughly 7 units, from 29.9 to 37.2) and E3 (roughly 5 units, from 32.3 to 37.4) are greater. An increase of 1 unit might make little difference in the larger scale configuration, but not in the smaller one. In fact, drive, *d*, improves performance by 38% in E1 across the modelled range (an average of over 6% per parameter setting), only 16% in E3 (average below 3%).

The objective of these experiments is to compare the effects on performance of the chosen behaviours under different environmental conditions. It is therefore more interesting and useful to focus on the effects of the behaviours in relation to the size of the 'single organization' modelled. The values on the *y*-axes therefore receive little further attention.
Facit: Support for CTS due to stronger positive impact on median performance of seizure of best-perceived opportunities in the more dynamic environmental category E1.

#4.2. *Relationship between persistence, p, and performance, X*

Results below show no discernable causal effect of persistence, *p*, on performance, X under the same conditions i.e. in all three environments with the other behaviours, dp^rc, fixed. There is no significant increase or decrease in median performance across the range of *p* settings (average increase per parameter setting of less than 1%).
Facit: New insight for CTS – there is no observable impact on median performance of abandonment of worst-perceived opportunities in the more dynamic environmental category E1, using CTS-SIM.

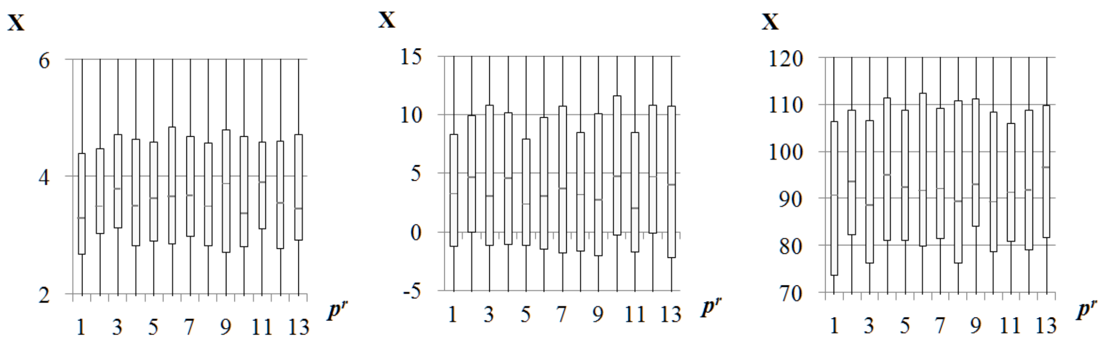


a) E1 (tfrc: hhhh) *b) E2 (tfrc: lhm$^+$m)* *c) E3 (tfrc: llll)*

Fig. 5.22. Effects of *p* on X in different environments
(Runs 200; Length 100 ticks)

#4.3. *Relationship between renewal of perceptions, p^r, and performance,* X

Simulation outcomes (over 13 parameter settings) also show no discernable causal effect of renewal of perceptions, p^r, on performance, X, for any of the environments[81]. There is no significant increase or decrease in median performance across the range of p^r settings (again average increase per parameter setting of less than 1%).
Facit: New insight for CTS – there is no observable impact on median performance of renewing perceptions in the more dynamic environmental category E1, using CTS-SIM.



a) E1 (tfrc: hhhh) *b) E2 (tfrc: lhm$^+$m)* *c) E3 (tfrc: llll)*

Fig. 5.23. Effects of p^r on X in different environments
(Runs 200; Length 100 ticks)

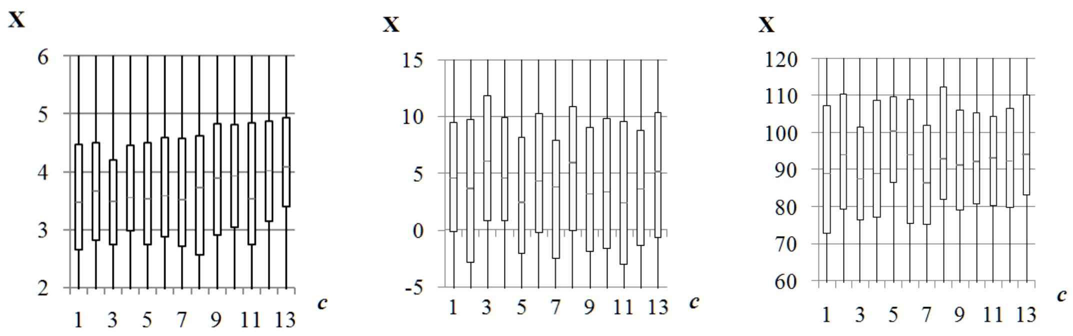
#4.4. *Relationship between initial commitment, c, and performance,* X

Finally, outcomes show a small, positive effect of initial commitment, *c*, on

[81] This seems reasonable given the *role of p^r* assumption (Section 5.2.3).

performance, X, but only in E1 (average median increase of 1 - 2% per parameter setting). Note that in each of the experiments there are considerable overlaps in the inter-quartile ranges. So although positive effects of drive and initial commitment on median performance are observable, these effects are far from assured. This fits with many observations of CAS and CAS models. The cohesion and size of bird flocks always differ (Wilensky, 1998) as do the ‘waves’ of crowds in football stadiums.

Facit: Some support for CTS due to discernable positive impact on median performance of retention of newly-seized opportunities in the more dynamic environmental category E1.



a) E1 (tfrc: hhhh) *b) E2 (tfrc: lhm$^+$m)* *c) E3 (tfrc:llll)*

Fig. 5.24. Effects of *c* on X in different environments
(Runs 200; Length 100 ticks)

5.3.2 Experiment #5: *Examining the relationship between individual opportunism and organizational performance under different conditions of environmental dynamism*

Having observed the positive effects of drive, *d*, and initial commitment, *c*, on overall performance, X, I turn to the effects of adopting different threshold values (see Decision criterion assumption, Section 5.2.3). Recall that agents could end up selecting the same number of opportunities in spite of different levels of drive, due to different thresholds.

This directly addresses the main question of the research: *How does distributed, opportunistic behaviour in dynamic CTS-type environments benefit the organization as a whole, if not the individual decision-makers themselves?* Here I investigate if and how the model privileges opportunism in all environmental configurations and whether any of those configurations supports less adventurous behaviour instead.

In this experiment I model opportunism as a strategic posture or orientation. The opportunistic strategist or decision-maker is more enterprising, and therefore has a high threshold for opportunity seizure and abandonment. Opportunistic agents therefore tend toward seizure and away from abandonment. Agents that tend toward both opportunity seizure and abandonment do both more readily, so I call them 'activists'. Other agents that tend away from opportunity seizure and toward abandonment are more cautious. I test the effects on performance of these different strategic postures under the same environmental conditions as before.

A *high seizure-tolerance* (*s-t*) is understood to be *at or near zero* (break-even, P = 0) i.e. the organization's minimum requirement for survival. A low tolerance is understood to be *above* that i.e. selection of opportunities only with high perceived values. Conversely, a *low abandonment-threshold* (*a-t*) *would be at zero,* a high threshold *below* that. This allows for four strategic decision-making categories:

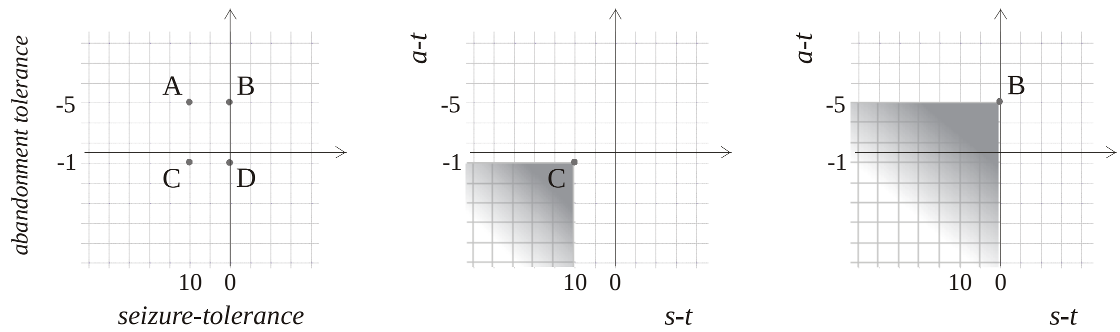
A: low seizure, high abandonment tolerance (low *s-t*, high *a-t*).
B: high seizure, high abandonment tolerance (high *s-t*, high *a-t*).
C: low seizure, low abandonment tolerance (low *s-t*, low *a-t*).
D: high seizure, low abandonment tolerance (high *s-t*, low *a-t*).

B is therefore the most opportunistic posture, D the activist posture, and C the most cautious. These are represented in Fig. 5.25*a* below. Strategic postures A, B, C and D are identifiable by their thresholds, points beyond which the respective strategist would not be willing to go[82].

A and B have high abandonment thresholds, *a-t*, set at minus 5. C and D have low abandonment thresholds, set at minus 1 (at or near break-even). B and D have high seizure thresholds, *s-t*, set at zero, A and C low seizure thresholds, set at 10. Note that tolerance thresholds increase along the *x* and *y* axes in Fig. 5.25, which means that *speed* of seizure *increases* along the *x*-axis and speed of abandonment *decreases* along the *y*-axis.

Strategist C, therefore, would only regard opportunities in the grey zone to be worthy of exploitation, Fig. 5.25*b*, whereas strategist B would be willing to expand outward from the origin due to higher tolerance thresholds on both axes, Fig. 5.25*c*. Hence, C is the least adventurous, already abandoning opportunities at or near break-even and selecting only above that, and B is the most adventurous, already selecting at break-even and abandoning only below that, Fig. 5.25*a*. D is the most selective strategist, already selecting and abandoning opportunities at or near break-even, while A is the opposite, hands-off, neither in a hurry to seize or abandon, Fig. 5.25*b*.

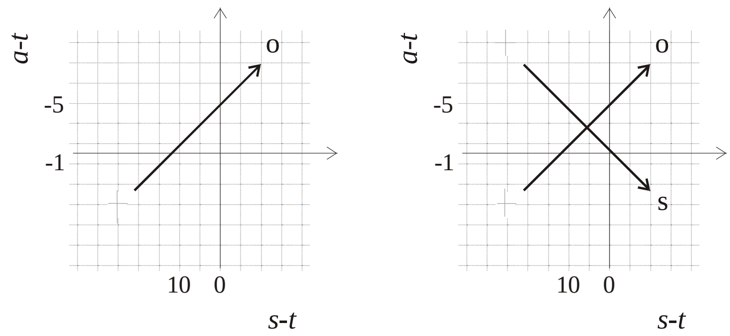
[82] These thresholds can be likened to the reference points used by individuals when evaluating choices according to Prospect Theory (Tversky and Kahnemann, 1986).



a) A, B, C, D tolerances *b) selection 'zone' for C* *c) selection 'zone' for B*

Fig. 5.25. Opportunity seizure and abandonment tolerance levels
(seizure-tolerance, *s-t*, on the *x*-axis and abandonment-tolerance, *a-t*, on the *y*-axis)

Moving up to the right, decision-making becomes progressively more enterprising, while moving down to the right, decision-making becomes progressively more selective.



a) increasing opportunism *b) increasing selection*

Fig. 5.26. Opportunism in terms of opportunity seizure and abandonment tolerances

Aim

The aim is to test whether opportunistic behaviour improves performance. If so, is it the case for all three of the environmental configurations? I test the effects of the four different strategic orientations (A, B, C, and D) on performance, X, in each of the above environments E1 (*tfrc: hhhh*), E2 (*tfrc:* $lhm^{+}m$) and E3 (*tfrc: llll)*. Here I vary the agents' thresholds, this also not having been done in this manner before.

Given that agents attempt to align themselves with the exogenous environment (see Section 5.2.5), one would expect the most enterprising strategic orientation, B, to impact performance positively when the environment is munificent. However, as observed in Fig.

4.22, highly dynamic environments are not always munificent. Nevertheless, as observed in Fig. 5.11, agents operating in more dynamic environments can perform successfully in spite of a lack of munificence. This fits with earlier studies (Eisenhardt and Sull, 2001; Baum and Wally, 2003).

Does increased *seizure-tolerance*, like *drive* in the previous simulations, improve performance in highly dynamic environments? Does increased *abandonment-tolerance*, like *persistence*, have no observable effect on performance in highly dynamic environments? Does increased *opportunism* (increased seizure and abandonment tolerance) improve performance in highly dynamic environments, or are there environmental conditions in which less adventurous or more selective strategies are better?

Due to the different effects of drive and persistence on performance (findings from Experiment #4), and hence the need to distinguish between behaviours that apply to perceived new opportunities vis-à-vis currently exploited ones, I first tested the effects on performance of different seizure-tolerances and different abandonment-tolerances separately. I then tested their effects on performance in combination, in search of the best strategic orientation overall.

I continue to focus on the indicators of dispersion, inter-quartile ranges and medians.

Parameters, settings

This experiment called for an extension of CTS-SIM. I capture the abovementioned thresholds through sliders for seizure and abandonment tolerances, *s-t* and *a-t*, as in Table 5.3 below.

Slider	Range	A	B	C	D
seize-val 1	0 to 10	10	1	10	1
abandon-val -1	-1 to -5	-5	-5	-1	-1

Table 5.3. Table showing seizure and abandonment tolerances for strategies A, B, C and D

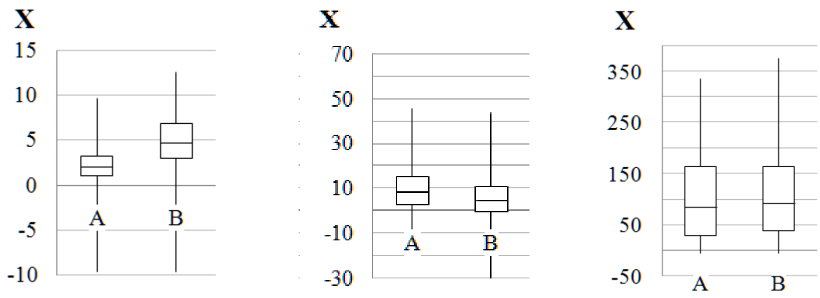
All other parameter settings for this batch of experiments remained the same as for the previous batch, as did the length and number of simulation runs. Settings for dpp^rc are fixed.

Outcomes, observations

<u>#5.1. *Effect of increased seizure-tolerance on performance*</u>

For strategy B (opportunist) there is a greater increase in performance due to a seizure-oriented approach to opportunity-transitioning in E1 (median increase: 36%, Fig. 5.27*a*) than in E3 (median increase: 8%, Fig. 5.27*c*). Higher *s-t* with *a-t* fixed is preferable in E1 and E3, but not E2 (Fig. 5.27*b*). CTS-SIM outcomes also favour a seizure-oriented approach at lower levels of abandonment-tolerance (D and C).

Facit: Support for CTS due to stronger positive impact on performance of increased seizure-tolerance in the more dynamic environmental category E1 i.e. conditional on an increase in all the drivers of the environment.



a) *E1 (tfrc: hhhh)* b) *E2 (tfrc: $lhm^{+}m$)* c) *E3 (tfrc: llll)*

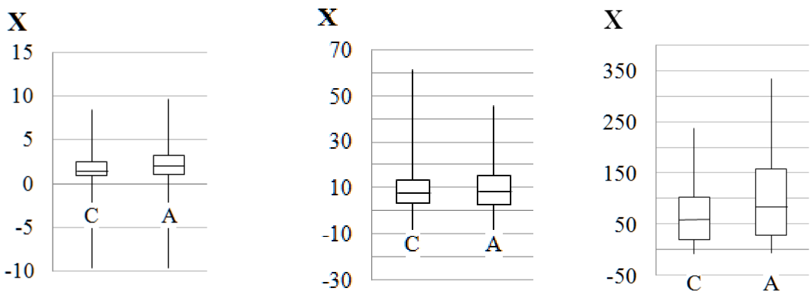
Fig. 5.27. Performance with differing seizure-tolerance levels (A and B)

#5.2. *Effect of increased abandonment-tolerance on performance*

For strategy A there is an increase in performance due to a retention-oriented (threat-tolerant) approach to opportunity-transitioning in E1 (median increase: 25% from 1.64 to 2.06, Fig. 5.28*a*) and in E3 (median increase: 52% from 56 to 86, Fig. 5.28*c*). Higher *a-t* with *s-t* fixed is preferable in E1 and E3, not in E2 (Fig. 5.28*b*). CTS-SIM outcomes also favour a threat-tolerant approach at higher levels of seizure-tolerance (B and D).

The positive impact on performance of seizure-tolerance over abandonment-tolerance is also clear by comparing the medians and non-overlapping inter-quartile ranges in Fig. 5.27*a* with those in Fig. 5.28*a*.

Facit: New insight for CTS due to positive, though weaker, impact of higher abandonment-tolerance than higher seizure-tolerance on performance, in the more dynamic environmental category E1.



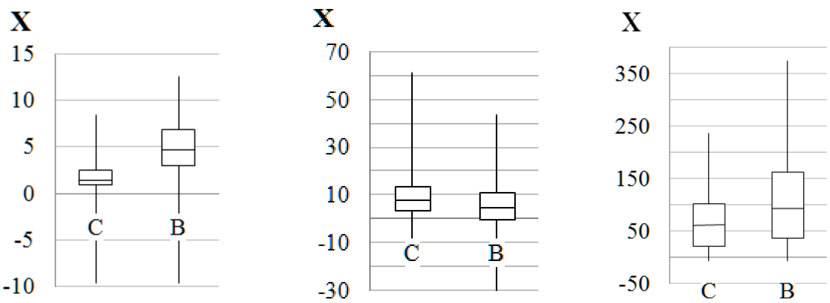
a) E1 (tfrc: hhhh) *b) E2 (tfrc: lhm⁺m)* *c) E3 (tfrc: llll)*

Fig. 5.28. Performance with different abandonment-tolerance levels (A and C)

#5.3. *Effect of opportunism on performance*

CTS-SIM favours a more adventurous approach (higher *s-t* and *a-t*) to opportunity-transitioning in E1 and E3 (Figs. 5.29*a* and *c*), not in E2 (Fig. 5.29*b*). Performance under decision criterion B is better than C. However, it is only clear in E1 (note the strong overlap of the inter-quartile range in E3).

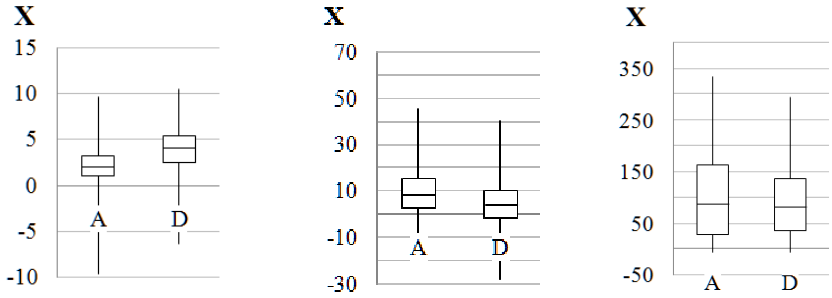
Facit: Support for CTS due to the strong positive effect of opportunism (in terms of increased seizure and abandonment tolerance levels) on performance in the more dynamic environmental category E1.



a) E1 (tfrc: hhhh) *b) E2 (tfrc: lhm⁺m)* *c) E3 (tfrc: llll)*

Fig. 5.29. Performance with increased opportunism (B) i.e. higher *s-t* and *a-t* values

CTS-SIM also favours a more *selective* approach to opportunity-transitioning, but only in E1 (Fig. 5.30*a*). Performance under decision criterion D is better than A i.e. seizure-tolerance causes greater performance improvement than abandonment-tolerance. But this is not the case in E2 or E3 (Figs. 5.30*b* and *c*). In other words a combination of higher *s-t* (faster seizure) and lower *a-t* (faster abandonment) is preferable in E1, not in E2 or E3.



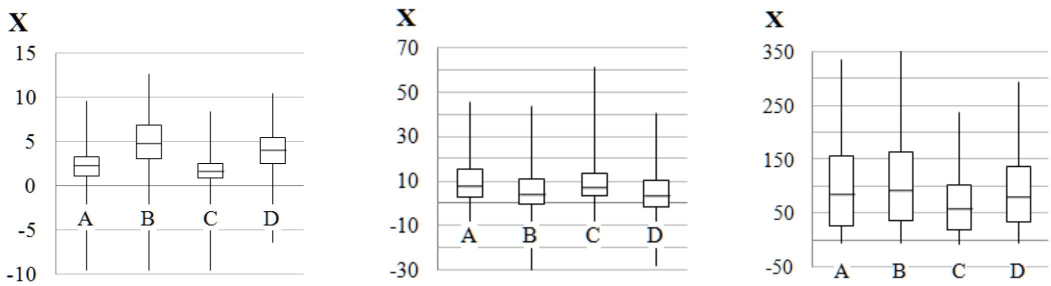
a) E1 (tfrc: hhhh) *b) E2 (tfrc: lhm⁺m)* *c) E3 (tfrc: llll)*

Fig. 5.30. Performance with different seizure *and* abandonment-tolerance levels (A, D)

In sum, Fig. 5.31 below shows how the four strategic orientations compare in the three environmental configurations tested:

1) E1: favours faster seizure (performance of B, D > A, C) and slower abandonment (B > D, A > C); favours faster seizure over slower abandonment (D > A).
2) E2: favours slower seizure (A, C > B, D) regardless of abandonment (A ≈ C, B ≈ D).
3) E3: favours faster seizure (B > A, D > C) and slower abandonment (B > D, A > C); does not favour faster seizure over slower abandonment, since performance of D is not greater than A.

Note that even though the individual agents are programmed to pursue their best-perceived opportunities in the highly dynamic environmental category E1, the performance outcome may be very poor and capable of bringing the organization down (see negative minimum values for X at all tolerance levels in Fig. 5.31*a*). However, generally speaking, all four postures produce positive median performance outcomes, even in E2.



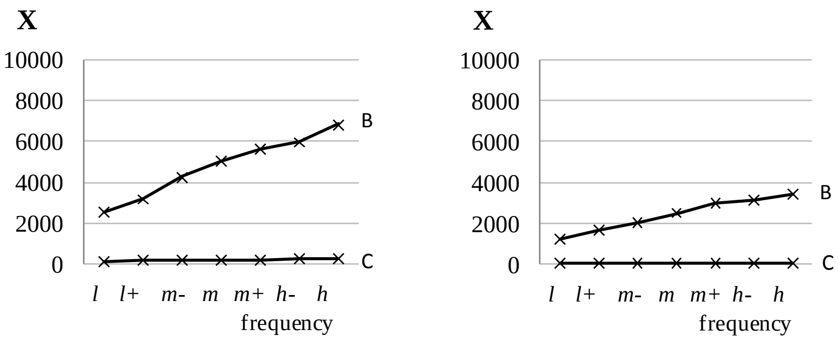
a) E1 (tfrc: hhhh) *b) E2 (tfrc: lhm⁺m)* *c) E3 (tfrc: llll)*

Fig. 5.31. Summary performance of different strategic orientations

#5.4. *Role of frequency, f, in the opportunism-performance relationship*

The outcomes of Experiments 1 - 3 (Chapter 4) showed that the flow of opportunities into the environment (frequency, *f*) cannot assure increased environmental munificence. Therefore, although frequency, *f*, is a key driver of environmental munificence, it is only one ingredient of successful performance. The experiments conducted in this research prompt further interesting questions, one in particular: *What is the effect of opportunism on performance in highly dynamic environments, specifically as it relates to the flow of opportunities into the environment?* This question also seems predestined for investigation using CTS-SIM.

The graphs below are an interesting way of conveying the relationship between frequency, opportunism and (median) performance at otherwise high levels of dynamism (*trc: hhh*). Outcomes of simulations shown in Fig. 5.32 shows that the more adventurous approach, B, places 'the organization' on a higher and steeper performance trajectory than a cautious approach, C (for both flow assumptions). Opportunism shows itself to be a way of exploiting the increased flow of opportunities into highly dynamic environments. In other words, opportunism thrives off increased opportunity flows.

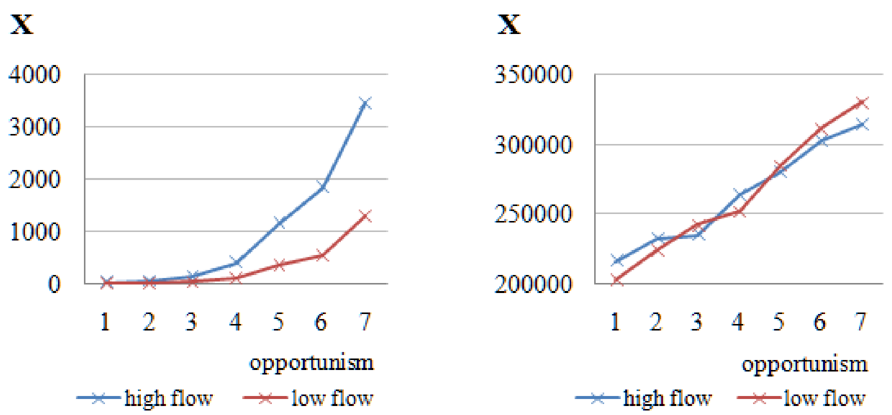


a) Flow assumption 1 *b) Flow assumption 2*

Fig. 5.32. Role of *f* in the opportunism-performance relationship
(comparing strategic orientations B and C at high levels of dynamism, *trc: hhh*)

Recall that in CTS-SIM increased opportunity flows, *f*, do not automatically cause an increase in environmental munificence. At low levels of transience and change, frequency does not play a major role. For CTS-SIM an increase in frequency across the full range of parameter settings results in an insignificant increase in munificence when transience and change are low, as opposed to a large increase when they are high (Appendix A4, Rows 2 and 9, columns I and L). Opportunities are longer-lived and need less replenishment.

It is not possible to infer from the above simulation outcomes that the positive effect of opportunism on performance is a feature of the relationship specific to highly dynamic environments. However, the simulation outcomes below do show that the efficacy of opportunism is specific to highly dynamic environments. Fig. 5.33 shows median performance at incrementally increased thresholds for opportunity seizure and abandonment. Opportunism is rewarded increasingly in the more dynamic configuration (*trc: hhh*), and thrives further off increased opportunity flows into the environment (Fig. 5.33*a*). However, Fig. 5.33*b* shows that a stable configuration privileges opportunism, but cannot benefit from increased flows due to low transience and change (*trc: lll*).



a) trc: hhh *b) trc: lll*

Fig. 5.33. Effect of opportunism on performance at different levels of dynamism (i.e. median performance)

Facit: Support for CTS, increased opportunism being rewarded increasingly at the higher driver levels tested and thriving off increased opportunity flows into the environment.

5.3.3 Experiment #6, *Testing extensions: payoff delays, heterogeneous skills and agent freedom*

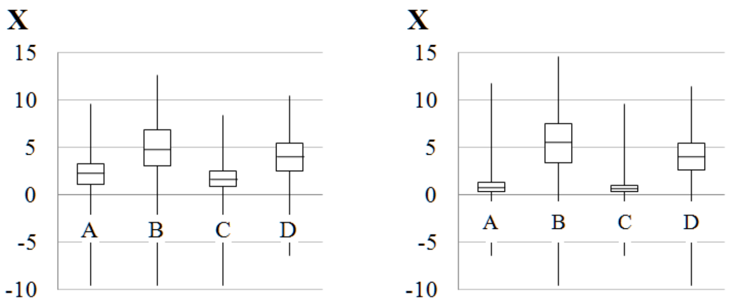
In this final batch of experiments I test the sensitivity of the outcomes of Experiment #5 to the minimal payoff delay simplification and the average-skills assumption (Section 5.2.3). As a closing explorative exercise, I conduct a search for patterns to successful transitioning among opportunities.

#6.1. *Payoff delays*

Throughout the simulation experiments conducted thus far, actions were assumed to follow intentions with minimal delay i.e. with payoffs, X, accruing within the next two, possibly three ticks (Section 5.2.3). The likely effects of this assumption for CTS-SIM are unclear, given the number of variables and the possibility of small shocks greatly affecting the system in nonlinear fashion.

I therefore tested for the sensitivity of outcomes to this assumption by running simulations for strategies A, B, C and D with parameters settings for 'maximal delays' (see Section 5.2.3) and compare outcomes with those for minimal delays, in the more dynamic environment, E1.

The simulation outcomes (Fig. 5.34 below) show no change in the findings of interest i.e. relative efficacy of A, B, C and D. The relative efficacy of opportunistic and activist orientations is underscored when delays are longer.

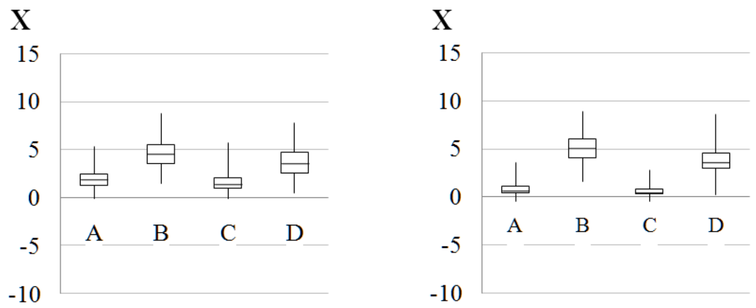


a) E1: min delays *b) E1: max delays*

Fig. 5.34. Performance with payoff delays

I controlled for the possibility that the effects of delays in E1 might be attenuated due to the long simulation time. I therefore ran simulations over a shorter period, again without any change in the findings of interest i.e. B > D > A > C (delays only impacting negatively on A and C in E1, Fig. 5.35).

Facit: Increased delays in the accrual of payoffs do not negatively affect performance at higher seizure-tolerances (B, D). (Increased delays do negatively affect performance at lower seizure-tolerances, A and C, an explanation for this being the reliance of these strategic postures on payoffs from fewer opportunities.)



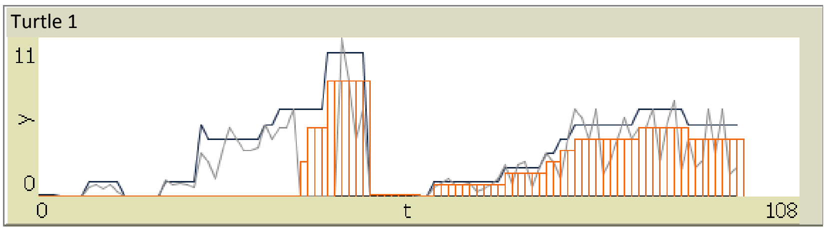
a) E1: min delays *b) E1: max delays*

Fig. 5.35. Performance with short run payoff delays
(12th - 24th tick)

<u>#6.2. *Heterogeneous skills*</u>

Recall that under the average skills assumption agent performance aligned with the environment as shown below (Fig. 5.11 again showing 80% skills level).

tfrc: *llll*



— potential (R) — perceived (P) — retained (X)

(Fig. 5.11. Exploitation based on average skills assumption)

To test the sensitivity of outcomes to this assumption, I extended the model to account for heterogeneous skills within the organization by randomizing *e-sk*, the advantage being that nothing within the selected range can confound outcomes. Fig. 5.36 shows agents executing opportunities differently, sometimes better, sometimes worse, and without advanced knowledge.

tfrc: *llll*

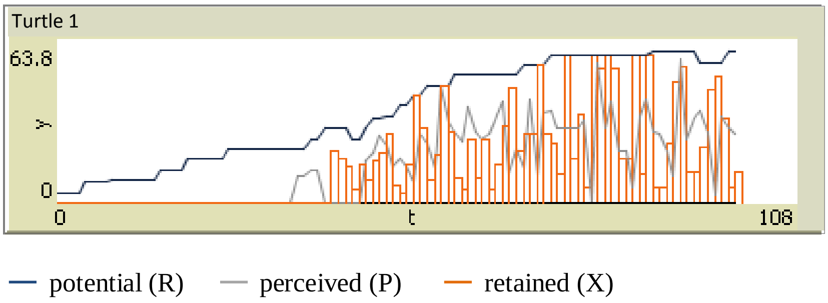
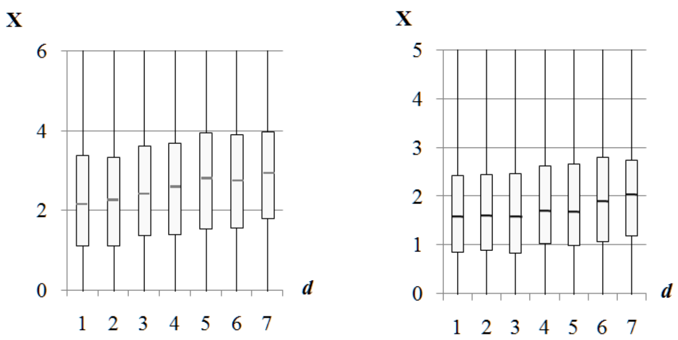


Fig. 5.36. Exploitation based on heterogeneous skills assumption

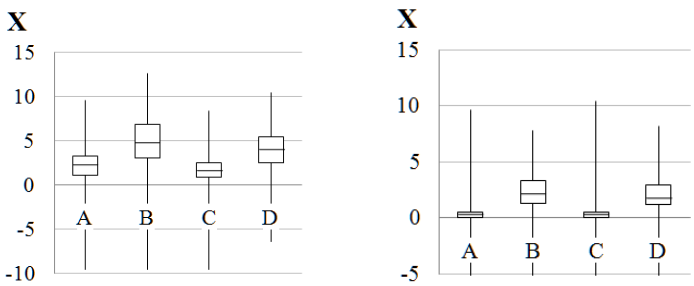
Simulation outcomes show that extending the model to account for heterogeneous skills still reveals a positive causal relationship between drive, *d*, and performance, X. At fixed average skills (80%) the improvement in median performance across the range of settings for drive was found to be 35% (increase from 2.15 to 2.91, Fig. 5.21*a*). Under random heterogeneous skills (range: 0 - 100%) the improvement is 24% (increase from 1.62 to 2.02, Fig. 5.37*b* below).



a) E1: e-sk (fixed) *b) E1: e-sk (random)*

Fig. 5.37. Effects of *d* on X (fixed average and random skills assumptions)

There was also no change in the relative efficacy of the strategies A, B, C and D under heterogeneous *e-sk* (Fig. 5.38 below):



a) E1: e-sk (fixed) *b) E1: e-sk (random)*

Fig. 5.38. Effects of A, B, C, D on X (fixed average and random skills in E1)

Facit: Modelling random execution skills is a robust way of showing that increased drive improves performance regardless of the skills assumption, no factor being able to disturb the results.

#6.3. *Agent freedom*

I complete the experimentation conducted in this research using CTS-SIM with a final investigation of the role of leadership constraint in CTS-type organizations. First, I test the effect on performance of unconstrained decision-making freedom. As indicated, an organization designed to enable people to tackle problems at the local level has been observed to improve performance (stylized fact 9). Because turtles have perceptions of what opportunities are on their patches, while the observer does not, the model is able to represent local decision making[83]. I therefore test whether lifting restrictions on the decision-making agents improves performance, expecting this to be the case. Then I test whether a pattern of opportunity seizure and abandonment emerges with successful agent opportunism.

One of the definitive assumptions of CAS noted in Chapter 2 is that they evolve through recombination. Groups and connections expand and contract such that, given a large number of agents and enough time, a power law arrangement of formations can result. Whereas the frequency distribution of large and small transitioning events could have an L-shape, given enough data, a log of the frequency and log of the size of transitioning events might reveal a power law signature, characterized by a negatively sloped line, or Zipf's Law.

Given the interdependence of agent decision-making in CTS, the continuous shifting and self-correcting among opportunities, one might expect such a pattern to emerge (Andriani and McKelvey, 2006). Do CTS systems also evolve toward critical states according to a

[83] Note that the model does not test the efficacy of distributed decision-making. For that, it would be necessary to endow the observer with a set of perceptions and transitioning rules too, and then to compare outcomes of one with the other i.e. of turtles vis-à-vis observer decision-making.

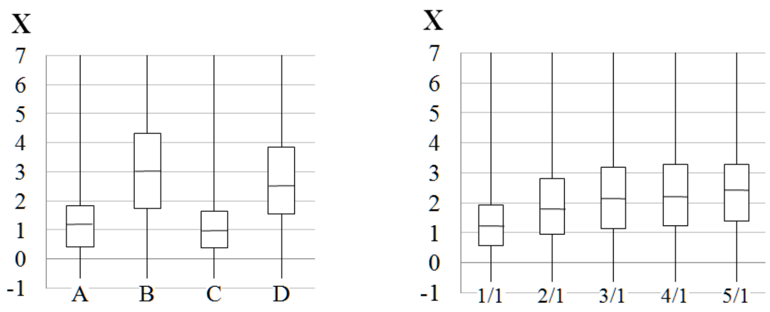
power law of opportunity-transitioning? This has not been explored before, and could prove useful to organizations because it points to the occurrence of more frequent ‘extreme events’, Andriani and McKelvey (2006, p. 4): “[T]here is good reason to believe that power law effects are also ubiquitous in organizations... researchers ignoring power law effects risk drawing false conclusions in their articles and promulgating useless advice to managers. This because what is important to most managers are the extremes they face, not the averages.”

To this extent, CTS-SIM could open up an interesting avenue for further research.

a) Effect of distributed decision-making on performance

For these experiments, the leadership of the CTS organization is represented by enabling the observer in CTS-SIM to restrict the number of opportunities turtles can seize and abandon at one time. This is controlled by means of sliders, one to constrain opportunity seizure, the other opportunity abandonment.

Simulation outcomes confirm that lifting restrictions on turtle freedom does improve performance. Fig. 5.39*b* shows incremental increases in X when freedom to seize and abandon opportunities is increased. It shows results starting with limiting agents to just one opportunity seizure and one abandonment per tick (1/1) and progressing to limits of five seizures and one abandonment (5/1).



a) Performance in E1

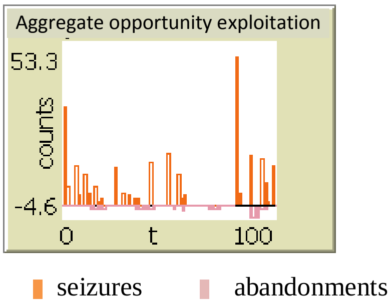
b) Performance in E1 with progressive agent freedom

Fig. 5.39. Comparing strategic orientations with increasing agent freedom
(Run lengths: 100 ticks; *e-sk* random)

Note that in Fig. 5.39*b* above, performance slows with increasing agent freedom. Given that agents without constraint seized up to fifty opportunities per tick and abandoned up to ten (Fig. 5.16), this raises the question as to how strategic orientation, captured in terms of agent tolerance levels (*s-t* and *a-t*) impacts on organizational performance compared with agent freedom, in terms of growth objectives. How do opportunistic decision-making agents, for example, operating within specific growth constraints perform in comparison with unconstrained, but less adventurous decision-making agents? Where are the bounds or tipping points? How are outcomes affected by the exogenous environment? CTS-SIM offers a platform for extension and future experimentation that addresses these problems.

b) Opportunity-transitioning patterns

The bar chart (Fig. 5.16 shown again below for convenience) records counts of agent opportunity seizures and abandonments during a single simulation:



(Fig. 5.16. Counts of agent opportunity seizures and abandonments)

When restrictions on the speed of growth in CTS-SIM are limited to a single opportunity per tick and to five opportunities per tick (Fig. 5.40*b*), no pattern is evident in a log-log plot of agent transitioning:

a) Seize-count: 1 *b) Seize-count: 5*

Fig. 5.40. Restricted opportunity transitioning behaviour
(i.e. with limited seizures and abandonments, *x*-axis)

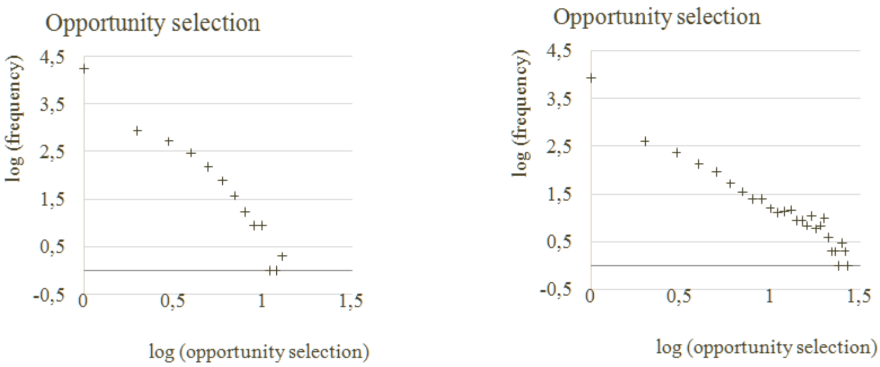
However, this changes when restrictions are lifted and agents are permitted to seize and abandon freely, as was the case in all of the previous experiments conducted in this chapter. Here a negatively sloped straight line does emerge. Fig. 5.41*a* produces fewer observations than Fig. 5.41*b*, the latter being a simulation of transitioning behaviour with a higher selection tolerance.

a) Decision criterion A *b) Decision criterion B*

Fig. 5.41. Opportunity transitioning behaviour for strategic orientations A, B

The negatively sloped straight line above (Fig. 5.41*b*) appears to tail off (bottom right). When the restriction on the size of the opportunity field (400 cells) is lifted (i.e. 2500 cells), the characteristic bushy tail begins to emerge (Fig 5.42*b*).

The negative slope suggests that the number of opportunities seized or abandoned simultaneously is inversely proportional to the frequency: the smaller the transitioning event (in terms of the number of opportunities), the more often its occurrence. The bushy tail points to an emphasis on the number of large transitioning events (when there is sufficient data).



a) Decision criterion B
Field size: 400 cells

b) Decision criterion B
Field size: 2500 cells

Fig. 5.42. Unrestricted opportunity transitioning behaviour on different size fields

A power law signature is currently considered a necessary but not a sufficient condition for a power law relation (Mitzenmacher, 2009). The emerging CTS literature and CTS-SIM point strongly to the efficacy of opportunity-transitioning behaviours on performance in more dynamic environments. Fitting and 'validating' the transitioning curve with power law signature revealed by CTS-SIM is therefore an interesting area for future research.

Facit: Simulation outcomes confirm that lifting restrictions on decision-making freedom improves performance and leads to opportunity-transitioning patterns that carry a power law signature.

Summary of Experiments 4 - 6 and main implications

The general aim of this chapter was to extend the model to capture the main features of opportunity-based behaviours in a useful and interesting manner, and then to examine their impact on performance in more dynamic CTS environments.

The simulation outcomes in this chapter provide much-needed support for the link between strategy and performance in CTS environments; they complement research using other methods (Eisenhardt and Sull, 2001; Wirtz, Mathieu and Schilke, 2007), in particular overcoming the limitations of small samples; they add depth in clarity regarding the impact of transitioning behaviours on performance in the environments tested; and they open up some interesting and useful avenues of future research. These are typical outcomes for this type of research.

The preliminary experiments conducted in Section 5.3 confirmed the susceptibility to error of inferences made from small sample sizes for this type of research; the test of run length confirmed the potential for meaningful cross-sectional observations, but for larger sample sizes; and the scope test showed that outcomes may be of interest to organizations exploiting few or many opportunities, both before and after some growth has taken place. The need for larger sample sizes supports this method of research.

Simulation outcomes (Experiment #4) showed that an increase in agent drive is more likely than otherwise to result in increased performance in each of the environments tested. The same applies to initial commitment, but this depends on the environment i.e. is only the case in E1 (*tfrc: hhhh*). For the other simulations, it does not appear to matter how decision-makers behave i.e. neither persistence nor perception renewal affect performance, at least not in the environments tested, and in the absence of changes in the other behaviours.

These simulation outcomes offer support for CTS based on the notion that successful strategists are highly driven in more dynamic markets. However, it does not support this for all environments with increased dynamism. As indicated in Chapter 4, further investigation of the state-space is necessary before making such a claim. The findings are particularly useful given the decrease in munificence associated with E1 (*tfrc: hhhh*).

The simulation outcomes also draw out the need to carefully distinguish between drive and persistence, given their different impacts on performance, and the need to distinguish between persistence and initial commitment. Under the conditions tested, willingness to *seize new* opportunities (drive) and to *retain newly seized* opportunities (initial commitment) can positively affect performance, unlike willingness to *abandon the worst perceived, currently exploited,* opportunities (persistence).

Simulation outcomes also point to a need for more clarity when referring to the renewal of perceptions. There are two related concepts at work, one being the renewal of beliefs or expectations about the scope of opportunity potential, the other being the renewal of beliefs or expectations about the *value of opportunity potential*. CTS-SIM captures the former in terms of uncertainty, U, the latter as renewal of perceptions, p^r. Both are forms of alertness or attention, both well-documented concepts. But uncertainty impacts the 'scope' of attention, while perception impacts the 'accuracy' of attention. CTS-SIM shows that the former can impact performance in unpredictable environments, but the latter is, by definition, futile. Simulation outcomes using CTS-SIM squeeze out the distinction.

It was also useful to further deconstruct opportunism into seizure-tolerance and abandonment-tolerance (Experiment #5). This reveals the need to distinguish between the two for their different impacts on performance in the dynamic environments tested. Like increased conviction (drive, initial commitment), increased tolerance thresholds (seizure and abandonment tolerance) can positively affect performance over time, particularly at high driver levels for opportunity flow and change.

Simulations outcomes add strength to the contention that distributed heterogeneous opportunistic decision-making improves overall performance in CTS environments, when opportunities are diverse, transient, uncertain and continuously changing. Simulations outcomes support suggestions that successful performance is internally driven, in spite of unpredictable environments.

Outcomes also add strength to the observed efficacy of increased opportunism in CTS environments, while pointing to the need to continue the search for environmental configurations in which this might not be the case. This research reveals that even at high levels of flow into the environment, slowed change and transience are enough to induce a less adventurous posture. Such configurations show no long-term pattern and reward lower seizure and abandonment-tolerance levels.

Results of Experiment #4 - 5 generate the following propositions.

At high levels of flow and change:

P5 The scope of managerial attention to opportunities, not the renewal of perceptions of currently exploited opportunities, can increase organizational performance in unpredictable environments.

P6 Faster seizure and retention of new and best-perceived opportunities (drive, initial commitment and seizure-tolerance) have greater positive effects on organizational performance than slower abandonment of currently exploited and worst-perceived opportunities (persistence and abandonment-tolerance).

P7 Opportunism in the form of increased conviction and tolerance levels at the managerial level improves organizational performance increasingly while thriving off increased opportunity flows into the environment.

Simulation outcomes (Experiment #6) also confirm the efficacy of unconstrained decision-making in CTS environments. However, they raise interesting questions about the strength of effects on performance of unconstrained decision-making vis-à-vis different strategic orientations. There is a tension between constrained but opportunistic decision-making and unconstrained but less adventurous decision-making which could reveal bounds and tipping points. Unconstrained opportunity-transitioning behaviour in CTS-SIM also follows a pattern that points to an emphasis on extreme transitioning events. The model opens up the possibility of adding to the evidence in favour of the ubiquity of power law behaviour in CAS. Results of Experiment #6 generate two further propositions.

At high levels of flow and change:

P8 There is a tension between the effects on organizational performance of leadership constraint and opportunism at the distributed decision-making level.

P9 Unconstrained decision-making is linked with an emphasis on extreme opportunity-transitioning.

5.4 Facilitating evaluation: CTS-SIM

With the aim of inspiring critical discussion and ongoing scientific work, the workings of the model extensions in this chapter were again carefully described. The underlying epistemological assumptions of the model were also addressed in an effort to demonstrate sensitivity to the concerns of different methodological perspectives in strategic management.

As before, the agent facility, the random number facility and the flexible GUI are the main features of NetLogo that help overcome the three main assumptions of homogeneity, independence and equilibrium. In these model extensions, it is the active, heterogeneous decision-making agents dispersed across the grid, combined with the facility of representing leadership constraint via the observer and the flexibility of random numbers that better address the heterogeneity, uncertainty and unpredictability typical of CTS systems.

The methods and toolkit also enabled a more explicit treatment of time than in traditional models. As indicated, a way of tracking time in CTS-SIM is in terms of ticks and run lengths. For CTS, distributed decision-making in terms of opportunity-transitioning takes place in short timeframes (Bourgeois and Eisenhardt, 1988, Eisenhardt, 1989a; Baum and Wally, 2003). ‘Ticks’ therefore correspond to days or weeks. Leadership decision-making timeframes in terms of growth are longer-term. Since leadership constraints are not changed during simulations, run lengths would correspond to several quarters, perhaps longer, of business[84]. In this sense the hierarchical structure of CTS-SIM borrows off distributed artificial intelligence and off examinations of biological and social system structures in

[84] Note that simulation runs of 12 ticks were able to produce patterns (Section 5.3.1). Fixing *speed of growth*, *growth-limit* for 6 months to one year fits with estimates of SBU reviews/decisions (Mankins and Steele, 2006).

which the upper layers tend to involve processes that span longer intervals than the lower levels (Simon, 1962).

Again there were no obvious shortcomings in the software for construction and analysis of the extensions in this chapter, at least none that suggest another method or toolkit might have been better. The software program is not beyond improvement, however, an ongoing task for the developers[85]. Some suggestions for software improvement have resulted from this research (these relate to the speed of execution for larger grid sizes and the ease of labelling plots for presentation purposes).

The task of careful model description again involved a clear statement of the main objectives. Close attention was also paid to the parameters and ranges of the variables i.e. the agent opportunity-transitioning behaviours, $dpp^{r}c$, the strategic orientations A, B, C and D and their causal relationships with overall performance in terms of payoffs. Important assumptions were drawn out and specified, as were the designs of the experiments, the simulation runs and lengths.

Archiving and referencing was pursued as in the previous chapter, thereby fulfilling important prerequisites for ongoing scientific work. Also, until there is convergence on a common standard for model publication, the model 'pseudo-code' is to be made publicly available as recommended by Wilensky and Rand (2007).

In the next section I address the characteristics of the model as they relate to the stylized facts by which it was guided. This is followed by a further section which continues the comparison of CTS-SIM with Davis et al's model.

5.4.1 Characteristics of CTS-SIM: extensions and simulation outcomes

Given their power in overcoming the heroic assumptions, the claim is that state-spaces generated using ABMS are likely to be more credible than most other models. However, much still rests on the logic of the model in question. In the previous chapter I used the strategic management literature to guide construction of the environment (Barnett and Burgelman, 1996; Brown and Eisenhardt, 1997; Farjoun, 2002 etc.). I also used the entrepreneurship literature (the Intentions and Direction of the entrepreneurial process models; Sarasvathy et al, 2003; Shane and Eckhardt, 2003) and the contributions of CAS researchers (Holland, 1995; Anderson, 1999; McKelvey, 2004 etc.).

[85] No subsequent updates of the current version suggest that CTS-SIM would run differently. In fact, the previous upgrade slowed the model down without there being any noteworthy improvements for this model, hence it remains coded and runs in Version 3.1.5.

CTS-SIM agent characteristics

As indicated in Chapter 2, there is little credibility in the 'rational actor'. Decision-makers face all sorts of limitations (attention, comprehension, communication etc.), so they edit, simplify and try to serve their own interests. To the extent that CTS-SIM agents might find that no opportunity satisfies their criteria at a point in time, and therefore do not seize one, their behaviour fits with the notion of satisficing (March, 1994). Satisficing also suggests that decision-makers might not consider further alternatives once satisfied, even if those alternatives are better. CTS-SIM does not contradict this behaviour, considering that agents forego potentially better alternatives on the grid by not considering certain opportunities[86]. Agent decision-making behaviour follows that of its human counterparts, who tend to simplify the world into 'good enough and not good enough' (March and Olsen, 1976; March, 1994).

The model also borrows off the theory of limited attention (see Fig. 5.7), important to the study of CAS (stylized fact 8). Being able to control attention levels follows March's (1994) requirement for an explorative approach in changing circumstances. This implies a sort of probing in the unknown, and fits with multiple case study research into organizations deemed to operate in highly dynamic contexts e.g. Charles Schwab, Sun Microsystems (Brown and Eisenhardt, 1998).

These organizations were found to engage in and benefit from probes – from 'learning by doing', creating opportunities and discovering threats, and from inserting an 'element of randomness that freshens thinking' – which they use to incrementally shape strategic direction (Brown and Eisenhardt, 1998, p. 151). Although no learning components for CTS-SIM agents are specifically built into the model, other than a 'preparedness to act', the model caters for learning. Considering that the turtles, in spite of their imperfect perceptions, form perceptions and act from tick to tick during simulations, the model does not contradict observations that entrepreneurial learning is ceaseless, error-prone and path-dependent in nature (Choi, 1993a; Harper, 1996; Koppl and Minniti, 2003).

In this chapter CTS-SIM borrows further off the Intentions model. Krueger (2003) observes that decision-makers employ filters, constructs and measures based on perceptions rather than reality. This stems from the realization – notably March and Olson (1976), Tversky and Kahnemann (1986), Mintzberg (1987) – that strategy is not primarily based on economic rationality. In that sense agent perceptions, P, are a 'reflection of what common sense tells the manager' (Kriens, 2006).

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[86] This aspect of satisficing requires that the 'switched off' turtles outside attention limits are viewed as unable *and/or unwilling* to consider the opportunities they are situated on.

In fact, CTS-SIM agent perceptions, P, do not contest Sutcliffe and Huber's (1998) observations that people's views are a function both of what they observe and learn as well as of others' influences. By their account, perceptions would be initially heterogeneous, becoming progressively more homogeneous, but they note that this is balanced by the functional diversity of agents i.e. their different backgrounds and responsibilities.

The capture of heterogeneous agent perceptions via surprise in CTS-SIM is also supported by Mezias and Starbuck's (2003) observations that most problem solving does not depend on accurate current knowledge of situations. Effective action is not prevented by inaccuracy. This phenomenon is evident in CTS-SIM, growth emerging in spite of surprise, even at high levels of transience, frequency and change.

Understanding the role and importance of perceptions, P, is simpler than quantifying it for modelling purposes. The difficulty in capturing perceptions was circumvented through the capture of surprise, S, which is pervasive in CTS systems (stylized fact 8). Surprise is an important concept that 'deserves critical attention' (Cunha et al, 2006). Because of inherent uncertainty in organizational CAS, Cunha et al (2006, p. 319) note that "surprises should be a well established field of organizational research". To that end, treatment of surprise as central to CTS-SIM is a step in the right direction.

So for CTS-SIM decision-making agents (turtles) form their own opinions and act on them, the random number facility ensuring their heterogeneity (stylized fact 10). Recall that the 'observer requests the input of the turtles', compares their inputs (perceptions of opportunities) according to a set of criteria, and permits them to select and abandon (Section 5.2.4). So action takes place in line with their degree of freedom. Actions depend indirectly on the perceptions of the other turtles. Therefore, although the model abstracts away from the negotiation and coordination processes that take place in practice, transitioning decisions are effectively interdependent (stylized fact 9).

CTS-SIM agents have autonomous perceptions, but only enjoy a degree of decision-making autonomy, depending on the freedom granted by leadership. CTS builds on the suggestion that in practice decision-making should be autonomous and distributed and that there should be 'just enough' guidance from a central authority for quick response and temporary advantages through the generation of novelty (stylized fact 9).

CTS-SIM 'agent organization'

The simple structure of the CTS-SIM 'organization', consisting of an upper and lower level, follows that of a number of researchers (Sutcliffe and Huber, 1998; Eisenhardt and Sull, 2001; Siggelkow and Rivkin, 2005). For example, the upper level (the observer) is a way of characterizing Sutcliffe and Huber’s top management team, and can be understood to include the CEO and those managers considered to be part of his or her team. The lower level (turtles) is a way of characterizing Eisenhardt and Sull’s strategic business unit (SBU).

Following these characterizations, the domain of the SBUs, the niches they operate in, the way decision-makers make their living, is the context through which strategists (and CTS-SIM turtles) are able to shape the emergent nature of the organization. In other words, strategists at the upper hierarchical level, rather than shaping a pattern or building a position, shape the context from which it emerges, by influencing or constraining the agents (Anderson, 1999, Eisenhardt and Martin, 2000; Eisenhardt and Sull, 2001). CTS-SIM caters for this, in an abstract way, through the speed of growth slider which controls the number of opportunities turtles can seize and abandon at a time.

In practice some members of the organization might belong to both levels, but this does not change how opportunity-transitioning in CTS-SIM should be understood, namely as a combination of both top-down and bottom-up influences. This follows Chakravarthy and Lorange (2008, p. 14): “Strategic renewal requires both a top-down and bottom-up effort. Top management sets the broad vision for the firm and specifies the scope and pace of renewal. However, it is the firm’s entrepreneur-managers who shape its renewal strategies and take responsibility for their implementation.”

A reason for endowing the lower level agents (turtles) with the responsibility for individual transitioning decisions is because their human counterparts are purported to be sufficiently integrated with day-to-day operations to be given the authority for coordinating the ideas of individuals or groups at the peripheries of the organization. For CTS-SIM, the agents representing SBUs are understood to operate at the ‘coal face’, which is within the cells of the opportunity field.

Cunha and Cunha, 2006 (p. 843) summarize CTS structures thus: “Minimal structures are constituted by a clear strategic intention, an adequate number of simple rules and ample individual freedom. Strategic intention provides agents with a way to determine what strategic direction it makes sense to take and gives control a centrifugal nature, instead of the centripetal conformity enforced by ‘thicker’ structures – be they based on obtrusive direct supervision or unobtrusive cultural commitment.”

CTS-SIM agent - environment blurring

Emery and Trist (1965) draw attention to differences between the laws that describe connections between parts of the environment to each other and between those connecting parts of the organization to each other. They suggest that because there are boundaries or 'break points' it is not possible to merely reduce one to being part of the other[87]. This is a reminder that the components that shape the endogenous CTS-SIM environment should be integrated but distinguishable from those that shape the broader exogenous environment (stylized fact 2). This is analogous to integrating, but being able to distinguish between, the parts of a bicycle and the bicycle itself.

The soft notion of R, as a potential, means that agent action is required for its exploitation. Although R is externally driven, because it is defined as a 'potential', it can be viewed as a potential for creation, discovery or allocation. These actions would be impossible without potential. This enables the integration of the three views of entrepreneurial opportunity (Sarasvathy et al, 2003).

Whereas the variables for opportunity flows and change, *tfrc*, shape the exogenous CTS-SIM environment, the variables for agent opportunity-transitioning behaviours (attention, drive, tolerance etc.) shape the endogenous CTS-SIM environment. Since the agent actions that shape the endogenous environment are only possible within the environmental potential, R, part of R is shaped, and can be characterized, as much by the agents' behaviours as by the opportunity flows and change, *tfrc*. Environment and agents begin to blur.

The model is able to distinguish between these elements of the system, while integrating them and demonstrating their interdependencies. In this sense it answers calls to avoid a firm partitioning of environment and organization.

Research by Perry (1991) offers further grounds for critical discussion. Perry (p. 53) notes: "Aspirations are freely floating, and opportunity determines aspiration level". How do agent aspirations relate to CTS-SIM? Does the model capture the observed feedback loops between aspirations and opportunities? For CTS-SIM, opportunity potentials, R, are understood to impact perceptions, P (via surprise, S). Because the probability of seizure above a certain perceived value is shaped by drive, *d*, the effectiveness of drive is impacted by opportunity potential, R. So, during simulations the number of opportunities likely to be selected at a point in time depends partly on the munificence of the exogenous environment (see Fig. 4.11), and partly on agent drive (Fig. 5.21).

Taking aspirations (hopes and ambitions) as being likely to impact perceptions, is a way of understanding how CTS-SIM relates to the work of Perry: R influences agent drive, *d*, via perceptions, P, and hence via aspirations. Although not specifically built into the model, CTS-SIM therefore follows Perry's observations, perceptions integrating aspirations. Note that CTS-SIM does not allow opportunities to *determine* aspiration levels as suggested by

[87] These researchers cite the analogy of not being able to connect the laws that govern meteorological variables with the actions of an athlete sighting and throwing a javelin.

Perry. The interaction of the chosen variables and uncertainty suggests opportunities can only indirectly help to shape them. This follows the principles of complexity that attempt to explain the behaviour of CAS that are non-deterministic.

CTS-SIM performance outcomes

Morris (2005, p. 51) prefers to distinguish between opportunities and options, and to reserve the term opportunities for occasions that yield positive payoffs: “Opportunities are valuable occasions to improve organizational performance… an improved condition contains the seeds for further improvement, more options and future opportunities. A choice that prevents a business from seeking its goals or leads to a dead end is not an opportunity… [i.e.] outcomes *that tend to cut off future opportunities* such as a reputation for shoddy products, dishonest business dealings or violations of trust (own emphasis).”

Morris’s observations serve as a reminder that the CTS-SIM ‘field of opportunities’ is part opportunity, part threat. But can the model demonstrate how choices or outcomes can ‘cut off future opportunities’? It can. It should by now be clear that having formed their perceptions, agents then act, and by doing so exert influence on the duration and value of payoffs: they commit to certain opportunities and forego others. That way, they effectively (but unforeseeably) facilitate new opportunities and restrict the organization from pursuing other perhaps more lucrative ones.

CTS-SIM also manages the distinction between options and opportunities, superabundant opportunities being the ‘precipitators’ of choices. This permits the interpretation of opportunities as ‘a confluence of circumstances’ which leads to the choice and rejection of options (Morris, 2005) through their seizure and abandonment on the CTS-SIM grid.

Morris (2005, p. 51) also observes that “While opportunities may be everywhere, they are not always apparent, and, once missed, they are gone.” CTS-SIM follows this characterisation. First, the ubiquity of opportunities is modelled via the assurance that there is opportunity superabundance throughout simulations (stylized fact 12), demonstrated in Fig. 5.8. Second, the partial imperceptibility of opportunities is modelled via surprise and agent uncertainty (stylized facts 7 and 8), demonstrated in Figures 5.8 and 5.12. Third, the transience and disappearance of opportunities is modelled via the externally driven environment (stylized facts 3 - 5), demonstrated in Figs. 4.5 - 4.8.

So the main features of CTS-SIM are its interdependent decision-making agents (turtles), each with their various limitations and some degree of autonomy, simply structured and organized within an unpredictable, unstable environment. Bringing them together in a virtual context does illuminate causal dynamics and core processes of opportunity-transitioning in highly dynamic environments. However, it cannot generate specific, predictable organizational outcomes. Even imposing leadership constraints does not shield performance outcomes from the influence of environment and decision-making agents.

For Emery and Trist (1965), successful firm adaptation was not considered possible by constraining decision-makers. For them, doing so was merely a way of construing a complex, dynamic, externally driven environment in unrealistically stable terms. They indicated there may be a high price to pay for uncertainty reduction i.e. for placing constraints on the freedom of the system. Outcomes of CTS-SIM Experiment #6 support these observations, performance improving with increased agent freedom, *ceteris paribus*. These insights have produced recommendations that business strategists search for emergent patterns and abandon the pursuit of limit states.

Gilbert and Troitzsch (1999) point out that none of the elements of a model should completely control outcomes – as no element of CTS-SIM can. This is analogous to the path of a river, in which the trajectories of single molecules of water are not predictable, but the overall flow of the river within the banks is (Gribbin, 2004), or can at least be explained.

Kriens (2006 Podcast) singles out the importance of luck in timing by looking back at the performance of an organization operating in highly dynamic environments (Juniper Networks), where it seems their managers were ‘plain stupid during one five-year period and geniuses with foresight during another’. Figures 5.11 - 5.15 demonstrate how agent behaviour might be described in just the same way.

Still, successful performance on the CTS-SIM field is not purely a matter of luck. Outcomes of simulation runs are unique, but they exhibit some broad behavioral patterns. Performance is chance and some probability. This is typical of CAS (stylized facts 6, 10 and 11). As Eisenhardt points out (Podcast 2006), opportunity exploitation in a superabundant field is “not like an Easter egg hunt”, but about placing lots of bets and being an early (not necessarily the first) mover – rather than about the classic models such as key customers and strategic focus.

5.4.2 Model comparison

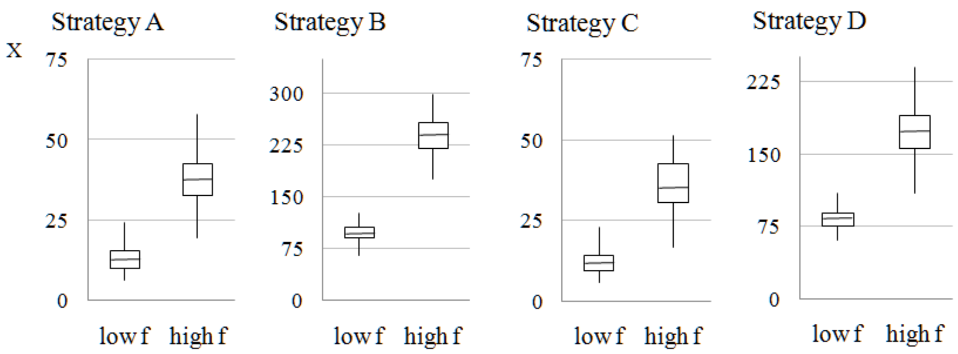
From Chapter 4, the only dimension of the Davis et al environment not modelled in the CTS-SIM environment was ambiguity or ‘difficulty in interpreting opportunities’. This is not specifically built into CTS-SIM. However the model addresses limitations in agents’ abilities to perceive and interpret via imperfect perceptions, P.

The Davis et al model does not specifically attempt to capture an exogenous environment. But simulation outcomes show (Davis et al, 2007, p. 48):

1) Velocity has a positive effect on performance.
2) Unpredictability has a predominantly negative effect on performance[88].

1) Positive effect of velocity on performance

Simulation outcomes using CTS-SIM replicate the positive effect of velocity on performance as per the Davis et al model (2007).



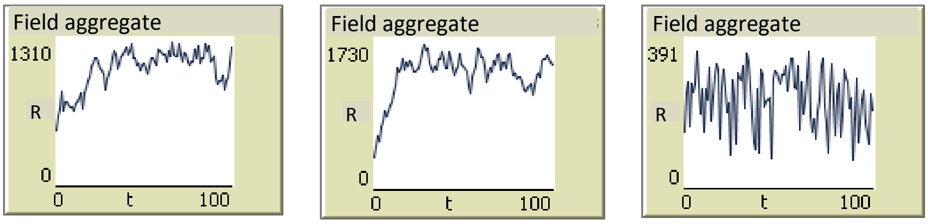
trc: hhh *(a)* *(b)* *(c)* *(d)*

Fig. 5.43. Effect on performance of increase in *f*

Note, however, that an increase in the pace of opportunity flow into the environment will only increase performance under certain behavioural conditions. An increase in flow accompanied by a shift in strategy from B to A or C could reduce performance (Fig. 5.43, note *y*-axes). Compare the performance of A at high flow, *f*, with B at low flow. In CTS-SIM, opportunity-based strategy can make a difference.

Note also that an increase in the pace of opportunity flow into the environment will only facilitate improved performance, *ceteris paribus*, if the other drivers of flow and change do not offset its positive effect on munificence. The utility of a rich CTS-SIM environment is apparent in the graphs below, where increased frequency, *f*, increases munificence (compare *y*-axes in Figs. 5.44*a* and *b*), but can be offset by the other drivers (compare *y*-axes in Figs. 5.44*b* and *c*).

[88] The impact on performance in the Davis et al model depends on the structure of the organization.



a) tfrc: mlmm
f = low

b) tfrc: mmmm
f = medium

c) tfrc: hhhh
f = high

Fig. 5.44. Effects of *f* on munificence

(*a* and *b* show an increase in munificence due to increased *f*, whereas *b* and *c* show *decreased* munificence due to increased *f* being offset by *trc)*

2) Predominantly negative effect of unpredictability on performance

Due to the unlikelihood of ever knowing all the inputs of a social system, and because CAS are susceptible to small changes in input parameters, surprise and unpredictability in this research are treated as features of CTS systems. CTS-SIM follows observations that favour agent efforts to orchestrate and respond rather than predict and control. CTS-SIM models a system in which the future cannot be predicted and surprise is a factor 'not amenable to removal' (Cunha et al, 2006). So in CTS-type environments, the nature and level of surprise (and therefore the renewal of perceptions, Experiment #4) does not affect performance (payoffs), whether positive, negative, absent or random. The Davis et al model has a different emphasis. Unpredictability is modelled as an environmental dimension, whereas in CTS-SIM unpredictability is linked with the agents and the system. However, the two can be reconciled.

From an exogenous perspective, CTS-SIM models the 'dissimilarity between the past and present' as emergent dynamism in terms of change associated with uncertainty (see Table 4.1). As indicated, a number of researchers have linked dynamism, pattern change, velocity and unpredictability (e.g. March and Simon, 1958; Dess and Beard, 1984; Baum and Wally, 2003). Eisenhardt and Martin (2000, p. 1111): "[W]hen markets are very dynamic or what is termed 'high velocity'…change becomes nonlinear and less predictable".

Simulation outcomes using CTS-SIM show that increased emergent dynamism can be predominantly associated with negative emergent munificence (see Table 4.5). Moreover, a move from environmental configuration E3, for example, to the more dynamic and less munificent E1 is associated with negative emergent performance (e.g. Fig. 5.27, note *y*-axis). Although this reconciles with the Davis et al model, CTS-SIM emphasises further causal mechanisms (environmental drivers, agent behaviours and strategic postures[89]) that affect the link between unpredictability and emergent performance.

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[89] Note that although performance in E1 is poorer than in E3 regardless of strategy (Figs. 5.21, 5.31), there is no claim here that opportunity-based strategy cannot compensate for finer increases in environmental dynamism.

6. DISCUSSION, CONCLUSION

All models are wrong, but some are useful
G.E.P. Box (1979)

I complete this research with a brief discussion and summary of the main findings, to the point of reaching conclusions. In Section 6.1, I summarize the principle aims and characteristics of CTS-SIM, and comment how to interpret, evaluate and use it as an autonomous tool for the further incremental development of emergent theory in the field of strategic management.

In Section 6.2, I note the key strengths of the model, in particular its ability to capture uncertain behaviour, its treatment of time, flow and coupling and its flexibility and potential for future experimentation. I also state the main outcomes of the research in relation to the goals of model construction and of testing and interpreting the simulation outcomes.

In Section 6.3, I close with the contribution to the fields of strategic management and entrepreneurship, which would not have been possible using another method of research.

There are the usual limitations, including tradeoffs that relate to model abstraction and those associated with one-stop modelling. I finish the chapter with a summary of recommendations for future research, including potentially useful model extensions and interesting questions for non-simulation scientists.

6.1 Interpreting CTS-SIM

I have tried in this research to remain sensitive to the underlying methodological implications of my choices, through extensive publication of the epistemological assumptions. In particular, I address the concerns of critical realists and the spectrum of constructivist tradition, whilst avoiding extreme views. Explicitly recognizing the contingent nature of organizational systems is an attempt to do two things simultaneously. One is to satisfy the strategic modelling standards of post-positivists by addressing complexity. The other is to satisfy the human behavioral standards of constructivists by avoiding claims of completeness and determinism, and emphasising the importance of treating the contribution of this research as a personal product.

By first constructing an exogenous environment, and then addressing the behaviours and strategies of the agents, I attempt to integrate the constructivist perspectives of R, the 'possible-world', with P and X, the perceptions and performance of agents. This approach adds an important 'sensitivity to context, history and perspective', which offers insights not possible from realist or empiricist research (Mir and Watson, 2001). From a strategic management perspective, the implication is that to understand what takes place inside organizations at least some regard for the contextual perceptions and behaviours of those involved is necessary.

When experimenting with the model my interpretations are subjective, targeted at understanding and causal explanation rather than prediction. Even so, explanations are not complete. As Byrne notes (2008), it is probably more helpful to accept the temporary and partial nature of such explanations – particularly in the social world – than to seek or claim complete understanding. Theoretical biology has also found it impossible to derive general principles from a single example (carbon-based life), and needs an 'ensemble of instances' to generalize (Byrne, 2008).

Still, models like CTS-SIM are a likely path to developing general theories about strategic behaviour in organizations. CTS-SIM itself can be used to go beyond investigating what, how or why things happened in given business situations, to what might happen. It can be used to explore ranges of circumstances and eventualities and hence to avoid some of the costs associated with trial-and-error experimentation.

Avoiding a purely deterministic view of the world, treating certain components as unknown, possibly unknowable, differentiates CTS-SIM from deterministic models. However, a model with a contingent, path-dependent emphasis need not eschew making sense of a possible world through exploratory modelling. It is therefore possible to avoid the theoretical risk that my intentions cannot compare with the interpretations of other simulation scientists.

The partially deterministic character of CTS-SIM, and its ability to reveal inaccuracies in the use of terms and constructs, is a feature that some researchers might associate with phenomenological hermeneutics. The RPX framework and the numerous attributes and variables addressed in the model point to an inclusive approach, not a narrow one, lending the model a degree of plausibility. Treating independently CTS, CTS-SIM and the 'real' organization operating in highly dynamic environmental contexts, means that CTS-SIM can be viewed as a bridge or mediator between CTS and the observed world, aligning it with the Semantic Conception of Theories.

Modelling the problem

The main aim of this research was to illuminate core processes and causal relationships in CTS-type systems using modelling and simulation. Addressing the central problem of *how heterogeneous, error-susceptible individual behaviour links to improved 'organizational' performance in the CTS context*, poses several challenges. These include, above all, addressing the role of time explicitly; the need for a consistent, integrated conceptualization of highly dynamic environments; the capture rather than reduction of uncertainty; the integration of decision-makers' imperfect perceptions, limited attention and heterogeneity; and integration of environment and organization.

To meet these challenges, a number of simplifications and abstractions were necessary. As a result, R, the 'realistic' world, is an abstraction of all factors external to the organization. Perceptions, P, are an abstraction. The model plays down the role of learning, negotiating, forming and dissolving relationships that inform the process of perception formation. Payoffs, X, are also an abstraction. Performance based on payoffs ignores liquidity in this version of the model, and abstracts away from the time value of money.

A result is that managers are represented as immobile, 'proto type' decision-making turtles. Interestingly, these abstractions are useful, though they come at a cost. It is not possible to model the entire, elusive and complicated process of opportunity-transitioning in highly dynamic environments. Generalization, accuracy and simplicity are tradeoffs. Simultaneous achievement of all three is not possible, yet as Siggelkow (2007, p. 21) notes: "If [models] were as complex as reality, they would not be useful." A more parsimonious model that builds in the fewest possible behaviours is generally easier to communicate and 'validate'.

Ormerod (2008) asserts that the search for a more abstract version is the whole point of science. The abstractions place CTS-SIM nearer the lower end of Ormerod's dimensionality scale i.e. alongside models with simple, satisficing agents and considerable abstraction of detail, vis-à-vis high dimensional models with high cognition agents and substantial detail.

However, although parsimony is important, there is richness in the areas where the research is focussed (Davis et al, 2007). Like the Davis et al model, CTS-SIM does not assume a fixed environment like many other simulation models. An environment with a single attribute does not permit the rich exploration of environmental dynamism that is a main aim of the research. As Einstein famously remarked, a model should be as simple as possible - but no more simple.

In this research, there was no reason to expect a very simple, elegant model to be particularly useful because the target is dominated by complex phenomena. Instead, model construction drew on numerous stylized facts from previous research, which delivers a rich ‘mix of ingredients’. The core ingredients were interdependent agents with constrainable decision-making autonomy, each with their individual limitations, simply structured and organized in an unpredictable, unstable environment.

Constructing a richer environment and investigating a number of transitioning behaviours delivered benefits. Modelling externally driven environments populated by decision-making agents helps to distinguish between challenges to successful performance caused by unpredictability (driven by the interaction of opportunity flows and change), and those caused by agent limitations. Modelling both drive and persistence, conviction and tolerance, adds depth and clarity to the opportunity-transitioning process. It illuminates the nature of transitioning behaviours and distinguishes between behaviours affecting the seizure of new opportunities vis-à-vis those affecting the retention of current ones.

The more inclusive approach to model construction opens up an interesting state-space not investigated in this manner before. Yet despite the opportunity for more breadth of exploration, experimentation remained focussed on the main research question. It was therefore not possible, for example, to address the full scope of the environment. An environment driven by four variables for flow and change creates a behaviour space too large to test fully in such a research project without compromising other research goals.

However, Experiments 1 - 3 (Chapter 4) enabled me to proceed toward the main goal of the research and to utilize the evidence from those simulation outcomes. It was possible (and necessary) to focus the research on two or three environmental configurations and ultimately on just two tolerance levels for seizure and abandonment. Fixing or ignoring the other variables did not mean overlooking them. An example was that of fixing the driver levels of the environment and the agent behaviours, dpp^rc, in Experiments 5 and 6. Doing this simplifies the analysis and interpretation of outcomes, and is a useful reminder when making claims about the model.

In short, model complexity as always is a virtue and a weakness: it can help explain stability and change, but it places large attention demands on the reader who has to “process and integrate the wide variety of seemingly disparate theories and constructs employed.” (Ocasio, 1997, p. 204). As noted, Schelling’s widely cited urban residential segregation model is recognized for its contribution to housing patterns and racial dynamics as well as to computation modelling in the social sciences, although it is understood that not all of the most significant variables were captured. Some models focus on complex behaviour from more simple models and others on simple behaviour from more complex assumptions (Marney and Tarbert, 2000).

Integrating the features or 'ingredients' of CTS-SIM using ABMS is a coherent way of following the epistemological shift from mechanistic toward organic principles in the field of strategic management. It does not require uncertainty reduction. Following Bankes et al (2002), the requirement in this research was to resist the motivation to 'limit the uncertainties to the detriment of the scientific value of results'. Therefore, like building laboratory equipment, it was possible to opt for more parameters, variables and switches as a way of increasing CTS-SIM's utility. That way it was possible to declare numerous dimensions of uncertainty. The outcome was the generation of 'perpetual novelty', which undermines prediction but not the emergence of recurrent patterns in the complex unfolding sequences (Holland, 1998).

The integration of randomness also helped to guide this model into lesser-known areas. It may not be possible to predict a certain outcome using CTS-SIM, but by isolating and varying certain variables while fixing others, it is possible to illuminate core behaviours and better understand them.

Being able to do this also drew out the differences between these differently driven environments. Running large numbers of simulations in noisy environments by isolating and varying these dimensions provides some interesting and meaningful results. It draws out the trade-off between clarity of expression and precision (typical of formal, quantitative approaches) and power of expression and descriptiveness (typical of qualitative modelling approaches), central to all modelling research.

Modelling complexity

CTS-SIM helps the observer to look directly, at an abstract level, into some of the dynamics of organizations operating in highly dynamic environments, permitting inspection of some of the elements of the system 'before it becomes shrouded in complexity' (Byrne, 1998). The utility of the model does not rely on the identification of causal factors of aggregate outcomes. The utility of CTS-SIM typically lies in the aggregate outcomes that emerge due to the *evolving interactions* of the environmental drivers and the agents (turtles) at the lower level (Anderson, 1999).

CTS-SIM shows how the drivers of the environment are shaped as much by one another as they are by their parameter settings. In Chapter 4, the frequency variable, *f*, for example, can only affect the path of the aggregate environmental potential, R, when a patch value is zero. Its parameter setting is subordinated to that condition. Each of the other drivers affects zero patch values, directly or indirectly, ultimately transience, *t*. At the same time (literally), transience can only affect R when there is a flow of opportunities into the environment caused by frequency, *f*.

The lower level decision-making agents in CTS-SIM cannot control the drivers of the exogenous environment, R. However, they can affect the duration of exploited opportunities, for example by their abandonment-tolerance. Their behaviour does affect the environment of the 'organization of agents' even though it cannot change the external drivers, *tfrc*. This is the blurring of environment and agents described in Section 5.4.1 (stylized fact 14).

Modelling agents' perceptions via surprise, and placing limits on their attention, means that they operate in partially self-constructed environments. How effectively they construct their environments becomes evident as simulations unfold. Outcomes are driven internally, externally and by luck. Any argument that the path to success starts internally has the effect of playing down the importance of the other drivers. It also has the effect of disregarding the notion that environments are partially internally constructed. Modelling complexity as emergent, from the bottom up, brings home the difficulty with dichotomizing interactive variables.

For CTS-SIM the interim, evolving and emergent behaviours rather than the end states of the system are of most interest. This is typical of ABMS, experimentation focusing on aggregate outcomes as they unfold. For CTS-SIM, the focus is away from collective behavioural optimization. Its potential utility in this context is for leaders of organizations or SBUs who need to know about the possible and likely consequences for firm performance of certain decision-making behaviours in certain environments.

The suggestion is that if agents focus on the drivers of opportunity flow and change and manage their affairs at the rule level, as opposed to the aggregate outcome level, there is a likelihood of affecting 'organizational' performance in a particular way i.e. with some level of increased probability. If managers can identify the levels and triggers of transience, of opportunity duration and change in their environments, and understand how their behaviours can affect performance, in particular their drive, commitment, and their tolerance levels for seizure and abandonment vis-à-vis their persistence and perception renewal, they improve their chances of success.

Furthermore, when leadership imposes or lifts constraints on the decision-making agents, aggregate transitioning and performance patterns develop that are difficult to observe in practice. Because CTS-SIM can generate massive amounts of data, when constraints are lifted it shows transitioning with a power law signature not seen before. Such outcomes can result when complementing traditional methods with new ones. Traditional methods like case studies offer incremental progress, which can be a slow process. In this regard, North and Macal (2007) point out the usefulness of a model that can compress and expand time.

Important to the theoretical arguments for developing CTS using CTS-SIM is not listing or causally ordering the variables that shape the exogenous environment and agent behaviours etc. Instead, it is illuminating how they can be expected to affect performance in certain ways, supporting arguments in favour of opportunism – and in some contexts, caution. It is an elegant way of evaluating why entrepreneurs base their ‘best judgments in a world of incessant change’ on their estimations of expected profits and losses. It helps explain why one pirate commander currently operating off Somalia’s shores claims pirates hijack ships ‘every opportunity they get’[90].

The environment and the decision-makers generate the energy that runs CTS-SIM. It is the opportunity flows and the turtle commitment to action from which pattern and structure emerge. This touches on an important area of research. Self-organization for CTS-SIM is the result of emergent outcomes, not of linear feedback but of higher-order, non-linear processes that are difficult or impossible to model using equation-based methods. A continual energy flow into the system is required. As Anderson (1999, p. 223) notes, “studies of how managers energize organizations have been divorced from inquiries into how pattern and structure emerge and evolve… Understanding the causes and consequences of injecting energy into an evolving network of agents is an important topic for further research.”

6.2 Summary of outcomes

In pursuing the main intriguing question that directed this research, CTS-SIM takes a step forward in addressing some of the issues of concern raised by strategic management and entrepreneurship researchers. It attempts to address the difficulty in modelling change and uncertainty as they unfold over time, treats error and surprise as features of the opportunity exploitation process, and blurs the distinction between environment and agent. It separates process from outcome by modelling drivers of dynamism and munificence and decision-makers with limitations, and enables the observation of emergent outcomes otherwise often hidden from view.

[90] Sugule Ali, pirate commander (Source: Time Magazine, February, 2009).

Given that the locus of opportunity discovery or creation lies with people, it is sensitive to aspects of cognitive psychology e.g. insights about intentions, perceptions, strategic issue categorization. For the same reason it adopts a heterogeneous, multi-agent framework. Addressing these issues using ABMS is useful in a world constrained by linear thinkers who are unable to imagine all of the possibilities a CAS can exhibit, or to understand the full effects of interactions through their mental models.

Chapter 2 listed a number of reasons for modelling (Epstein, 2008). Several proved themselves in this research. CTS-SIM illuminates the impacts of the chosen external drivers and agent opportunism on CTS-type environments and systems. It illuminates core uncertainties, for example in the estimation of growth in terms of increased opportunity exploitation and the quantification of surprise. CTS-SIM also illuminates core dynamics of the opportunity-transitioning process, represented in the RPX framework and in the chosen environmental drivers and agent behaviours. The research also takes initial steps toward placing bounds on outcomes by testing the efficacy of opportunism in environmental configurations that differ in terms of the levels of their drivers.

CTS-SIM shows the apparently simple concept of 'transitioning among opportunities' to be complex, by showing the need to differentiate between awareness and perceptions of new perceived versus currently exploited opportunities, and between tolerance and conviction. It also shows the apparently complex concept of integrating exogenous and endogenous environments with all three views of opportunity exploitation, to be reasonably straightforward, facilitated by the 'soft' notion of R.

Further, CTS-SIM offers new directions for data collection, for example on what factors dominate the deaths of opportunities, and what factors dominate decision-makers' efforts to expand their attention limits. It also asks new questions e.g. 'What tensions or tipping points exist between opportunism and decision-making constraint?' and 'Can CTS systems evolve toward critical states according to a power law of opportunity-transitioning, toward which the model points?

Developing the model invoked a willingness to work incrementally from the simple to the complex. Allowing construction to be guided by numerous stylized facts produced a model which is quite challenging for readers to grasp. This is quite typical of such research. It is also a reflection of the tension between my roles as a modeller striving for simplicity at the expense of 'realism' and as a simulation scientist striving for 'realism' at the expense of simplicity (Carley, 2002).

Despite its richness, CTS-SIM focuses on specific issues and is directed, throughout the research, toward answering the main intriguing question. Honouring the bottom-up paradigm and benefiting from the powerful temporal aspect of ABMS opens up a useful and interesting environmental state-space abstract enough for experimentation. Running extensive simulations over selected parts of the state-space permits the emergence and observation of patterns in strategy-performance relationships that tend not to emerge in CAS from small samples.

Remaining focussed on the main problem helped to guide the process of model construction and description, necessary for evaluating the model. The outcome is a modelled environment that consists of a large and diverse set of fleeting opportunities, driven externally by continuous, stochastic flows and change. Running simulations of the environment gives rise to simultaneous uncertainties, unpredictability and nonlinearities and is highly sensitive to small changes in the drivers. Being able to change the parameter settings of the drivers and to observe the effects on dynamism and munificence underscores the utility of the model for extension and further investigation.

The CTS-SIM environment first pointed to the unlikelihood of reasonably attributing any efficacy of opportunism in CTS environments purely to an increased flow of opportunities into the environment. Although increased flows into the environment do improve munificence, for CTS-SIM they require accompanying high levels of transience and change. Even a small change in one of these is likely to undermine munificence.

The constructed CTS-SIM environment facilitated the observation of aggregate behaviours in a sufficiently simple way. Simulation outcomes indicated that, because high driver levels generally drain environmental munificence, something other than munificence might be required to explain successful performance in such environments. To that extent, the outcomes lent added support for the further investigation of the causal role of opportunistic behaviour in dynamic CTS environments.

The task that followed was to inhabit the environment with a simply structured organization of individual agents, to enable them to ‘form’ their own perceptions, yet also to model the organization such that their decisions and actions are in some way constrainable by a leadership level. For this to be possible, the agents needed to be highly interconnected and heterogeneous and to make errors that cause surprise. CTS-SIM, in an abstract way, specifically takes on board each of these characteristics yet, crucially, does not prevent the organization from somehow succeeding.

Simulation outcomes using the extended model offer support for the efficacy of distributed decision-maker opportunism in highly dynamic environments. For CTS-SIM, when opportunity flows into the environment are increased in isolation, performance does privilege opportunism. However, the research goes further in addressing the main question as to how modelled opportunistic behaviour in dynamic environments benefits the organization as a whole.

Following the deconstruction of the environment, the research led to the deconstruction of opportunism in the form of increased agent conviction and tolerance levels. Simulation outcomes support increased opportunism, but only in quite strictly CTS-type environmental configurations. Even at high levels of flow into the modelled environment, when change slows and transience is low, this can be enough to induce a less adventurous posture.

The sheer size of the modelled state-space, however, prevented a full investigation of all such possible configurations. Nevertheless, CTS-SIM is able to show that even small changes in the parameter settings of the drivers of opportunity flow and change are enough to send the environment off on a completely different trajectory – and possibly a roller-coaster ride not for the faint-hearted.

The deconstruction of aspects of opportunism, like the environment, generates some interesting propositions. Notably, simulation outcomes draw out the importance to overall performance of scope of attention over perception renewal in unpredictable environments, and of increased seizure and retention of new and best-perceived opportunities over increased abandonment of currently exploited and worst-perceived opportunities. They also point to a tension between leadership constraint on decision-making and decision-maker opportunism, and to an emphasis on extreme opportunity-transitioning when leadership constraints are lifted.

These are complex dynamics with many interacting variables, which ABMS, with its forced transparency and graphic features help to further illuminate and explain. CTS researchers recognize the importance of a clear understanding of such dynamics. In particular, the roles of the environmental drivers and decision-making behaviours in the opportunity-transitioning process.

Fig. 5.33 shows the effect of opportunistic decision-making on overall performance at different levels of dynamism, and Fig. 5.43 shows the effect on performance of an increase in opportunity flow into a highly dynamic CTS-SIM environment. These two figures are, in essence, the culmination of this research. They offer a focussed response to the main research problem. However, they are a small part of a systematic investigation and analysis of extensive simulation runs, so their utility depends on how well they are understood in the context of the rest of the research.

I summarize the strengths of CTS-SIM below, the key findings of the research and the main implications.

Main strengths of the model

1) Bottom-up model construction:
   For CTS-SIM this meant that attempting to directly capture such concepts as environmental dynamism and system complexity could be avoided. Instead, it was possible to base the environment and agents on simpler constructs and to use the strength of ABMS to allow these concepts to emerge in short virtual time spaces. This was useful, since the aim was to explore and understand short-term patterns and relationships between variables, as opposed to making forecasts.
   In principle, all that was needed was to describe the component behaviours, to demonstrate the connections between them, and investigate possible interventions.

2) Treatment of time:
   Synthesising the different perspectives of time, enabled CTS-SIM to capture interactions among the constituent parts in a manner consistent with management practice. Rather than a discrete, one-off formulation, the system and environment are both inclusive and continuous. This allowed history to play a role.
   A clock-event-time perspective facilitated both temporal and event-based pacing of decisions and actions, which better illuminates how successful agents choose to persist with certain opportunities and not with others.

3) Integration:
   This research integrates contributions from more than one field and by using ABMS it facilitates the integration of numerous variables and constructs. Simulation outcomes reflect the emergence of behaviours based on the interdependence of the micro-level elements. The coupling of interdependence and the soft notion of R 'as a potential', helps to overcome the neoclassical problem of a firmly partitioned environment and organization. This follows calls from the field of strategic management for more dynamic, holistic models that sufficiently separate process from outcome, and calls from the field of entrepreneurship to integrate the three views of entrepreneurial opportunity pursuit.

4) Emergent complexity:
   The model does not attempt to mirror 'truth or reality', being based on stylized aspects of organizations operating in CTS contexts. However, it captures some of the complexity of such organizations. By allowing important concepts (e.g. opportunity

duration and organizational performance) to emerge as a result of interactions among the variables, CTS-SIM differs from other related and concurrently developed models where such components are captured using a top-down approach e.g. Siggelkow and Rivkin's (2005) parameterization of complexity, and Davis et al's treatment of environmental dimensions.

5) Clarity:

   An important strength of CTS-SIM is its ability to connect actions and events on a grid. This helps to illuminate and explain why particular outcomes emerge. These are the result of the 'unforgiving rigor of a computer program', rhetoric being unable to deviate it from its rule-based consequences (North and Macal, 2007). This is what exposes the importance for CTS of more precise terminology – the usefulness in distinguishing between agent conviction and tolerance for example – without the risk of assumptions failing to surface at all, which can be common in other methods. The model therefore exposes itself to critical analysis and interpretation and therefore runs less risk of taking overoptimistic steps in the direction of the truth. This forced transparency supports strength of method.

6) Experimentation:

   CTS-SIM helps overcome one of the main difficulties in researching organizations, by taking control of the time, size and number of rules and variables involved. By using the power of the computer, it was possible to explore many plausible paths and structures, which is difficult using other methods. That way it was possible to observe patterns at the aggregate opportunity level, and over time, which not only generated minimum and maximum data observations but also more meaningful inter-quartile ranges and central tendencies. The model permitted a wider range of experimentation involving interactions and nonlinear effects than traditional statistical techniques or inductive case studies methods. This meant it was possible to find boundary conditions for certain environments and steep thresholds that revealed a tension between the micro-level elements of the environment, transience and reversal. Systematic experimentation also supports strength of method.

7) Flexibility, extensibility:

   CTS-SIM overcomes a weakness of many other models by enabling the user to change the 'chemistry of the ingredients'. By adopting a modifiable approach, the model escapes unwanted constraints. It was therefore possible to approximate ranges of behaviours without being overly deterministic (as with equation-based models) and thereby to capture some of the uncertainty associated with CTS systems, and to facilitate changing performance metrics necessary for this research (unlike genetic algorithms).

It was also possible to contribute to the quality of the model by ensuring its extensibility through choice of a suitable toolkit (for its flexible GUI, compatibility etc.) and by developing simple abstract, but integrative concepts and definitions (e.g. for R, P and X). Reasonable human and material costs (hard- and software requirements) also contribute to the extensibility of the model[91]. The model can also generate massive amounts of data at less cost than other forms of research.

Key research findings

The research produced several interesting and useful outcomes. Most important, simulations outcomes using CTS-SIM are able to demonstrate how heterogeneous, opportunistic decision-making by individual agents can improve their overall performance in CTS-type contexts, in spite of the pervasiveness of error and surprise at the individual level. They support the intuitive argument that this is likely to have something to do with the flow of opportunities into highly dynamic environments. However, they also illuminate complex dynamics, sensitivities to small shocks and to assumptions, thereby defying simple explanations.

1. Construction of the environment:

   The initial phase of construction produced a rich environment by ‘unpacking’ the drivers of dynamism and munificence. The model is based on a simple conceptualization of the environment as made up of opportunity flows and change. It can be characterised by important stylized facts: a large and diverse set of opportunity potentials, driven externally by continuous, stochastic flows and change.

   The modelled environment illuminates the interactive relationship among the causal variables that drive environmental dynamism and munificence, and it enables the user to change the parameters of the drivers and thereby influence this emergent behaviour. This was something of a requirement for the ongoing research.

[91] Although indications that both strategic management research and modelling are likely to be time-consuming (Balogun et al, 2003) were also borne out in this research, a significant portion of these costs has already been absorbed into the construction and experimentation with this version of CTS-SIM.

Main simulation outcomes (Chapter 4)

Experiments 1 - 3 showed that increases in opportunity flows and change generally give rise to more dynamic and less munificent environments.

As expected, patterns generally only revealed themselves at an aggregate level and over time, thereby contributing to justification for the method used to generate them.

Simulation outcomes, however, also revealed sensitivities to the behaviours of the individuals, to small shocks caused by changes in the driver parameters, and to assumptions about what triggers the end of opportunities.

Most interesting perhaps, outcomes revealed tensions between the drivers that can cause behaviour to suppress all patterns, even at the aggregate level and over time. These interactions produce nonlinear path dependencies, sudden transitions and irregular patterns, with a mix of probability and behavioural unpredictability.

The interaction of the four chosen drivers opened up a state-space interesting and large enough to warrant further investigation of its behaviour.

These outcomes resulted in four propositions for the support and further development of CTS.

2. Construction of the extended model:

   The main phase of construction involved the further development of the simple RPX framework. It facilitates the integration of a ‘realistic’ externally driven environment (R), with agents that have autonomous, heterogeneous perceptions (P) and that perform by following an opportunity-based logic of constrainable action (X). The RPX framework is the platform for the integration of the three views of opportunity pursuit in the entrepreneurship literature and for the blurring of exogenous and endogenous environments.

   The extended model is also informed by important stylized facts: it is populated by perception-based decision-makers that are sub-rational but alert, and willing to choose among payoffs in a flexible and prompt manner; that form a ‘flexible constitution of agents’ and interact within the constraints of a simply structured ‘organization’; and whose actions cause surprise and error.

   This is useful because most models overlook the partial autonomy, limitations and heterogeneity of decision-makers, ignore the role of perceptions and surprise, and continue to firmly-partition environment and organization.

   The extended model illuminates some core dynamics of agent opportunity-transitioning in CTS-type environments. The research process also ultimately results in the deconstruction of opportunism into several behaviours and postures, and thereby shows the apparently simple concept of agent opportunity-transitioning to be complex.

Main simulation outcomes (Chapter 5)
Experiments 4 - 6 add strength to suggestions that the most successful performance is internally driven. They also add strength to suggestions that increased opportunism in CTS environments is efficacious, while pointing to the need to continue the search for environmental configurations in which this might not be the case. This research reveals that even at high levels of flow into the modelled environment, slowed change and low transience can be enough to induce a less adventurous agent posture.
Sensitivity tests also confirm the susceptibility to error of inferences made from small sample sizes for this type of research, which is useful particularly because demonstrating and explaining why opportunity seizure works well in dynamic, noisy, environments has been difficult. In CAS, patterns tend not to emerge from small samples.
Again, emergent performance patterns only revealed themselves over time and after many simulation runs, further justifying the method used to generate them.
Simulation outcomes draw out the different causal effects on performance of different dimensions of opportunism, notably those of agent conviction and tolerance levels regarding the seizure of new opportunities vis-à-vis the abandonment of currently exploited ones.
These outcomes led to several further propositions for the development of CTS.

Implications for researchers and managers

1. Support for emerging CTS
   a. *Opportunism, though unreliable for decision-making agents, 'can' work in CTS-type environments:*
   The sensitivity, complexity and uncertainty of the modelled environment and hence the likelihood of agent surprise and error, offers support for rewarding fast seizure and high average performances, for programming agents accordingly, to take risks to extend opportunities and not penalizing them for errors.
   They can be expected to seize more opportunities, but to perform worse on average.

CTS-SIM supports observations in favour of faster, more audacious opportunity seizure, and of slower abandonment in CTS-type environments. This facilitates growth and eking the last out of opportunities.

CTS-SIM draws out the importance of at least two other success factors besides opportunism: the levels of the drivers of the environment, and luck. These are quite capable of overriding the effects on agent performance of opportunism.

2. New insights for CTS
   a. *Research adds depth and clarity to CTS.*

      CTS-SIM draws out the sensitivity of CTS environments to lower level drivers of opportunities and of organizational performance to agent transitioning behaviours. Based on a conceptualization of the environment as consisting of opportunity flows and change, researchers should focus their attention on understanding the causal roles of the different drivers of emergent behaviours such as dynamism and munificence, and the factors that dominate how they are triggered, rather than on the (emergent) behaviours themselves.

      The model also draws out the distinction between well-documented opportunity-transitioning behaviours such as alertness, drive and opportunism. Each had positive implications for agent performance, but very different effects.

      Furthermore, although the model can be reconciled with that of Davis et al (2007) it emphasises deeper causal mechanisms (environmental drivers, agent behaviours and strategic postures) that affect the link between unpredictable environments, agent limitations and emergent agent performance.

      Modelling externally driven environments populated by decision-making agents helps to distinguish between challenges to successful performance caused by unpredictability (driven by flows and change) and those caused by agent limitations.

      Modelling both drive and persistence adds depth and clarity to the opportunity-transitioning process. It draws out the role and nature of transitioning behaviours and the distinction between those affecting the seizure of new opportunities vis-à-vis those affecting the retention of current ones.

   b. *Scope of agent attention beats accuracy of perception in unpredictable environments.*

      The model takes unpredictability to mean a partly unknowable future and unavoidable surprise. Simulation outcomes therefore suggest that the purpose of updating perceptions of opportunities is essentially to establish their emergence. This drowns out other putative reasons such as to assess their comparative promise or their fit with existing or expected capabilities.

The implication is that agent 'organizational' performance will benefit from efforts to increase attention rather than to improve accuracy of perceptions.

It also places bounds on the benefits of commitment to opportunities and strategic resolve.

c. *Distributed agent decision-making points to extreme opportunity-transitioning events*.

Simulations outcomes show that in highly dynamic environments unconstrained decision-making is likely to improve performance and result in transitioning behaviour with an emphasis on large numbers of seizures and abandonments, for which the agent 'organization' should prepare itself.

3. Key avenues for useful future research (see also Section 6.4)

a. *There is a need for full investigation of the environmental state-space*.

Investigations of sub-regions of the environmental state-space demonstrate high interdependence of the micro-level elements, sensitivity to certain assumptions and small shocks. This suggests that a bottom-up perspective is likely to be more useful in trying to understand important aggregate behaviours such as environmental dynamism and organizational performance.

Knowledge of the causes and effects of changes in opportunity flows on aggregate environmental behaviours is likely to affect perceptions of potential opportunity payoffs, so answers ought to be of particular interest to decision makers.

Until that knowledge is available, without a deeper understanding of the micro-level elements, there should be no rush to explanations or conclusions about successful performance in CTS-type systems.

b. *There is promise in the flexible, evolutionary, capture of opportunism*.

The current version of CTS-SIM does not account for altering strategies during individual simulation runs.

The potential usefulness of the model could be extended to cater for behavioural shifts e.g. for shifts toward opportunism in faster moving environments and away

in slower ones.
Extending the model to account for such observations might provide interesting insights and add to model utility.

c. *There is a need to explore and test tensions between opportunism and leadership constraint.*
Emery and Trist (1965) first suggested that there may be a high price to pay for uncertainty reduction, for placing constraints on the freedom of the system. Simulation outcomes offer robust support for the positive effect on performance of agent opportunism and unconstrained decision-making under specific conditions. This raises interesting questions: How do opportunistic decision-making agents operating within specific growth constraints perform compared with more cautious, less error-prone decision-making agents that are unconstrained? Where are the bounds or tipping points? What role does the externally driven environment play? CTS-SIM offers a platform for extension and testing of these problems.

d. *Utility of fitting and 'validating' transitioning patterns.*
Simulation outcomes show for the first time that unconstrained agent opportunity-transitioning results in a pattern of events with a power law signature.
Fitting and validating an emergent opportunity-transitioning distribution that conforms to a power law could add to the evidence in favour of arguments for the ubiquity of such patterns in CAS.

6.3 Contribution

Organizational theories receive criticism for not capturing all variables. However, if they are interesting or new, according to Sutton and Staw (1995), the standards used to evaluate them should be relaxed, not strengthened i.e. when data are illustrative rather than definitive. This fits with Whetten's (1989) observation that theories are often judged by their novelty and contemporary interest, and with van Maanen, Sørensen and Mitchell's (2007, p. 1145) assertion that "the aim of organizational and management research is to speculate, discover, and document, as well as to provisionally order, explain, and predict". These researchers call for some flexibility in connecting data and concepts and for allowing logic of discovery rather than purely validation.

van Maanen et al (2007) add that some theories attempt to provide covering laws that govern relationships among variables or constructs, others attempt to provide novel explanations or 'provoke a sort of unexpected enlightenment among knowledgeable readers' by conveying new, potentially useful constructs or exposing unsuspected relationships hitherto unknown. Still other theories attempt to use their methods to show the plausibility and presumed strength of various linkages in the 'constructed analytic narrative'. Funtowicz and Ravetz (1994, p. 4) suggest that to "wait until the relevant high-precision natural sciences were available before doing anything about global warming or species preservation would be a counsel of perfection indistinguishable from a counsel of despair… The task is to manage the uncertainties that are characteristic of each field so that information of the highest possible quality can be obtained from them."

This research uses ABMS to manage some of the uncertainties characteristic of opportunity transitioning in organizations. It conveys new, potentially useful constructs: an original fundamental framework, RPX; a novel conceptualization of an exogenous environment consisting of baseline elements that shape the dynamism and munificence of opportunity potentials; and an independent approach to identifying and choosing variables for capture.

This research answers a number of calls from other researchers. One is for an explicit treatment of time, where timing, speed and vigilance can obviously affect successful performance in highly dynamic markets. Another is for models that sufficiently separate process from outcome, that treat individuality, uncertainty, unpredictability, and hence error and surprise, as features of the opportunity exploitation process. Still another is for a consistent, integrated conceptualization of markets as made up of opportunity flows and change, and for the integration of the creation, discovery and allocation views of opportunity pursuit.

Most models overlook these issues, often treating time implicitly, markets as stable and predictable, ignoring the role of perceptions and firmly partitioning environment and organization. CTS-SIM treats time explicitly, takes steps toward the integration of the limited attention and 'sense-making' ability of decision-makers by means of a multi-agent framework. It treats error and surprise as features of the opportunity exploitation process, in so doing blurring the distinction between environment and individual. It also benefits from a toolkit with the flexibility and potential to address aspects of cognitive psychology in an ongoing manner.

Perhaps most important, the research takes agent-based simulation a step further by modelling organizational behaviour in terms of autonomous perception formation, but constrainable decision-making autonomy. Research efforts to examine and illuminate the relationship between individual opportunism and overall performance in CTS-type environments might eventually prove useful to organizations, since it can affect how they structure themselves and how they motivate and reward their people.

How opportunism succeeds in uncertain, dynamic, noisy, environments over time has been difficult to demonstrate and explain. This is because behavioural patterns are difficult to observe in practice. They tend not to emerge in CAS from small samples. Building a model and running extensive simulations has been a way of addressing this challenge. The outcome is a new synthesis of thought and experimentation that permits a form of empirical work not previously done.

The primary contribution of the research is the illumination of core dynamics and causal effects associated with the opportunity-transitioning process. The research reveals core uncertainties, demonstrates tradeoffs, shows the apparently simple to be complex and complex to be simple, and takes initial steps toward placing bounds on outcomes. This goes to the root of the research problem.

Insights into the opportunity-transitioning process are important, given their potentially close link to a major organizational activity, strategic decision making. They are important for the potential they have of placing organizations in highly uncertain and vulnerable positions due to the exploratory nature of the process.

It is nevertheless best not to view the research only in terms of its potential utility for developing CTS. Doing so distracts from the advantages of obtaining information about the model, target and theory during model construction and experimentation. Models are autonomous.

As an autonomous model, CTS-SIM offers guidance for ongoing data collection, raises interesting new questions and opens up useful avenues for ongoing research, including experimentation using extended versions of the model. CTS-SIM is an ‘electronic laboratory’ with explanatory power. As a platform for ongoing, aggressive experimentation, it opens up a way of implementing aspects of CTS systems previously thought impractical.

Although CTS-SIM builds on a novel framework and a novel conceptualization of the exogenous environment, these are responses to calls from other researchers. Previous scientific observations have closely guided its construction. The model is sensitive to different schools of thought, and every step has been taken to ensure that it is explicit, transparent, flexible and accessible, to attend to the requirements of users and to inspire and focus critical discussion.

6.4 Scope, limitations, and future research

The transparency of CTS-SIM makes it easier to review and analyze it and draw out its scope and limitations. This can also point the way to useful areas of future research, an additional expectation when conducting such research.

The research directly addresses decision-making in CTS-type organizations. The suggestion is that such organizations are innovative, knowledge-based, have looser forms of collaboration and fluid boundaries, distinguishing them from those that are asset-intensive, vertically integrated, with rigid boundaries and tight control over employees.

To that extent, this research should be relevant to growth-oriented firms operating in highly dynamic environments, those with higher 'clock-speeds', such as the computer, movie, semiconductor and cosmetics industries. It focuses away from organizations operating in more stable, slower moving industries, such as tobacco, petrochemicals, paper etc. There is no attempt to distinguish between agent behaviours that are typical of 'innovators', those that bring knowledge into the organization incrementally, and 'reproducers'.

CTS-SIM should also be more useful to young firms (to the extent that established firms have a tendency toward complacency), to small firms (to the extent that they are more innovative), and to large firms (to the extent that they are better able to leverage their capabilities). It most likely applies to dynamic firms that operate in environments where events are irregular, novelty high and horizons short, in which time and events are experienced as unpredictable and uncontrollable, and strategic orientation is apparently 'spasmodic' and temporal.

The model would most likely apply in environments where there is a burst of activity, such as the Internet bubble. Looking ahead, the model or extensions of it, might help shape behaviour in the expected energy technology revolution (Siebel, 2009). It may also have implications for other existing dynamic entities, including young people who in future might be tasked with self-employment and survival in turbulent times.

Different cultures have different relationships with time and events (Hofstede, 1991). Impatience may be as much a virtue as patience in relentlessly driven, 'short-termist' environments, where continuous growth, innovation, personal gratification, media stimulation etc. are important. To this extent opportunity-based strategies would apply more to Anglo-Saxon and the European societies or the USA, characterized by a preference for short-term results and outcomes, than Oriental and South East Asian societies that have tended to take a long-term view (Morden, 2007).

There is sometimes the need for a reminder that all models are partly artefact and that one of the main points of science is exploring and testing abstractions for what we can learn from them. Byrne (1998) makes the point that the difficulty with abstraction is that we have no way of predicting the importance of what has been excluded i.e. it may prove crucial later on. Abstractions come at a cost, Cilliers, (2000, p. 31): "We cannot make simple models of complex systems… If it is in the nature of the system to behave, at least sometimes, in novel and unpredictable ways, the model must also do so."

So abstractions are also flaws and constitute limitations, and therefore are also here explicitly acknowledged as such. Although abstractions are not an argument against models (Cilliers, 2000), researchers generally agree that reducing complexity and nonlinearity distorts our understanding of them, therefore calling for modesty when trying to understand complex systems.

CTS-SIM, like many models, is likely to be difficult to compare with other models. These difficulties could persist due to the model's differing theoretical goals and content and the lack of standard techniques for agent-based construction and experimentation. This might expose CTS-SIM to the risk of isolation and over-reliance on the stylized facts taken from other research, and therefore slow down the process of development, particularly for the one-stop modeller confronted with construction, observation, analysis and explanation of large state-spaces.

It is impossible to claim completeness for CTS-SIM, but more developed versions may replace false assumptions with plausible new features and descriptions. Although it can come at the cost of generality, I suggest here some additional steps toward higher model resolution and utility (besides those mentioned in Section 6.2):

1. *Recommendations using other research methods*:
   1.1. The relative growth assumption in this version of CTS-SIM (agents increase their field of attention in line with their ongoing performance) points to the usefulness of gathering data on the relationship between firm size, firm growth and strategies for increasing the scope of managerial attention in dynamic markets.
   1.2. Sensitivities of the exogenous CTS-SIM environment to its drivers also point to the usefulness of studies that are able to contribute to a deeper understanding of the factors that trigger the end of an opportunity in the CTS context.

2. *Potential model extensions*:
   2.1. Further deconstructing the model:
   There may be deeper micro-level variables than those chosen for this version of

CTS-SIM. For example, one need only ask what triggers the cession of opportunities. Suitable answers might lead to further questions about the factors behind those causes, a process that can go on *ad infinitum*[92].

2.2. Integrating group dynamics:

To coax out a transitioning pattern in Experiment #6, simulations were run using different size opportunity fields, and hence with different limits to numbers of agents. The simulations did not test for the possible effects of group dynamics, which points to a potential model extension. Siebers (2008)[93]: "In order to study the real effects of policy changes... you need the right level of heterogeneity of the agents… It is also important to remember that a group is not just a collection of individuals but develops its own dynamics. These might be different for different group sizes. Bigger groups might create additional dynamics…"

2.3. Refining agent behaviours:

In making the point that decision-making is best left to middle-managers, those at the nexus of strategy and tactics, Brown and Eisenhardt (1997, p. 66) write: By "[focussing] their quest on the best opportunities [these managers] pursue a small number of high-payoff areas – about 20-30% of all possible collaborative opportunities." Again, an extension of the model to specifically account for this observation might provide interesting insights and add to model usefulness.

2.4. Integrating resource scarcity:

Jacobides and Winter (2007, p. 1213) point out that entrepreneurs "are characteristically short of cash, and of the ability to convince others to provide it". Extending the model to account for resource scarcity might provide interesting insights.

3. *Facilitating ongoing evaluation*:

3.1. Using model comparison:

Model comparison is a useful way of addressing the risk of isolation, whether through different authors, languages, toolkits etc. This can help to demonstrate that the results of the original model were not chance (Windrum et al, 2007). To assist with this, I take on the recommendation of Wilensky and Rand (2007) to make the 'pseudo-code' publicly available, at least until there is convergence on a common standard for model publication.

[92] That would not necessarily disqualify earlier research. In the field of chemistry, for example, progress has depended on models based on atoms, without their composition mattering.

[93] SIMSOC e-mail communication, August, 2008.

To conclude, this research, by focussing on a complexity theory for strategy in highly dynamic environments, was compelled to build on contributions from outside of the field of strategic management. The expectation is that such contributions can benefit organizational theories by bringing inter-disciplinary insights and technology to bear on complex social processes in useful and interesting ways. Giddings (2008) notes that it is surprising that some sciences founded on the linear determinism of classical physics have adopted nonlinear computational modelling more rapidly than the behavioral sciences, especially considering that computers are able not only to multitask but also to multi-thread, which compensates researchers' weaknesses in addressing information-rich environments.

Being able to bring inter-disciplinary insights and technology to bear on complex social processes are exciting developments. To ignore them is to miss the opportunity for payoffs. Anderson (1999, p. 229) writes: "Organization theory has not yet caught up with the sophisticated tools that have emerged for analyzing the behavior of complex adaptive systems. We are not on the verge of a revolution that will render a century of organization theory obsolete, but remarkable new vistas are opening up, thanks to the melding of the science of complexity and organization theory and the increasing availability of new techniques for modelling nonlinear behavior. Those who take advantage of this opportunity will lead us to think in new ways about what kind of organizational data to gather and what kind of models to construct."

This research is a small, yet overdue step toward taking advantage of the opportunity to which Anderson pointed ten years ago.

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APPENDICES

A1. Abbreviations

ABMS	agent-based simulation and modeling
CAS	complex, adaptive systems
CTS	complexity theory of strategy
CTS-SIM	NetLogo simulation model
GUI	graphic user interface
SBU	strategic business unit
RPX	fundamental framework for CTS-SIM (R = real, P = perceived, X = exploited opportunities)
R	realistic net opportunity value
P	perceived net opportunity value
X	exploited portion of net realistic opportunity (= opportunity payoff)
S	surprise (CTS-SIM feature)
U	agent uncertainty (limited attention)
e-sk	agent execution skills

A2. Variables

Experiments 1 - 3:

Environment

t	transience of opportunity flows
f	frequency of opportunity flows
r	reversal (change in direction of change)
c	change in opportunity value

Experiment 4:

Agent behaviours

d	drive (willingness to seize best-perceived opportunities)
p	persistence (willingness to abandon worst-perceived opportunities)
p^r	perception renewal
c	initial commitment

Experiment 5:

Strategic tolerances

A	low seizure and high abandonment tolerance
B	high seizure and abandonment tolerance
C	low seizure and abandonment tolerance
D	high seizure and low abandonment tolerance

A3. Three approaches to strategy

	Traditional		Emerging
	Position	*Resources*	*Simple rules*
Strategic logic	Establish position	Leverage resources	Pursue opportunities
Strategic steps	Identify an attractive market Locate a defensible position Fortify and defend	Establish a vision Build resources Leverage across markets	Jump into the confusion Keep moving Seize opportunities Finish strong
Strategic question	Where should we be?	What should we be?	How should we proceed?
Source of advantage	Unique, valuable position with tightly integrated activity system	Unique, valuable, inimitable resources	Key processes and unique simple rules
Works best in	Slowly changing, well-structured markets	Moderately changing, well-structured markets	Rapidly changing, ambiguous markets
Duration of advantage	Sustained	Sustained	Unpredictable
Risk	It will be too difficult to alter position as conditions change	Company will be too slow to build new resources as conditions change	Managers will be too tentative in executing on promising opportunities
Performance goal	Profitability	Long-term dominance	Growth

(Source: Eisenhardt and Sull, 2001, p. 109)

A4. Effects of environmental drivers, *tfrc*, on dynamism and munificence

Table shows the individual effects on dynamism and munificence of each variable at a setting of *low* and *high*, at settings of low and high for the other drivers, and for both flow assumptions.

Example:
Column D, row 5, (10.8) shows dynamism at *tfrc: hhhl*.
Column E, row 5, (15.3) shows dynamism at *tfrc: hhhh*.
Hence an increase in dynamism of 41% (Column F, row 5,) caused by an increase in *c* at high levels of *tfr*.

			A	B	C	D	E	F	G	H	I	J	K	L
			Dynamism						**Munificence**					
			Driver levels: low			*Driver levels: high*			*Driver levels: low*			*Driver levels: high*		
			Variable setting			Variable setting			Variable setting			Variable setting		
		Variable	*l*	*h*	*effect*	*l*	*h*	*effect*	*l*	*h*	*effect*	*l*	*h*	*effect*
Assumption 1	1	*t*		11.0	1%	12.1		26%		1,490	-1%	110		-59%
	2	*f*		10.9	-1%	7.3		108%		1,547	2%	21		112%
	3	flows (*tf*)	10.9	10.9	0%	10.8	15.3	41%	1,510	1,542	2%	88	45	-49%
	4	*r*		10.6	-3%	30.6		-50%		1,548	3%	314		-86%
	5	*c*		11.1	1%	10.8		41%		156	-90%	1,537		-97%
	6	change (*rc*)		10.4	-4%	9.5		61%		87	-94%	1,578		-97%
	7	*tfrc*	10.9				15.3	40%	1,510				45	-97%
Assumption 2	8	*t*		10.6	3%	10.3		16%		1,505	-2%	-71		135%
	9	*f*		10.4	0%	6.0		99%		1,524	0%	13		94%
	10	flows (*tf*)	10.3	11.0	6%	8.7	11.9	38%	1,529	1,551	1%	-50	25	150%
	11	*r*		10.6	3%	39.3		-70%		1,546	1%	571		-96%
	12	*c*		21.5	109%	11.3		6%		704	-54%	1,513		-98%
	13	change (*rc*)		9.3	-10%	11.4		5%		-52	-103%	1,551		-98%
	15	*tfrc*	10.8				11.9	10%	1,529				25	-98%
	16	*c* (at low *r*)	10.3	10.6	3%	10.8	38.2	253%	1,539	1,546	0%	1,535	580	-62%

A4. Effects on dynamism and munificence of increases in environmental drivers
Note: figures for munificence are cumulative (in thousands)

Key observations:

1. Increased opportunity flow *into* the environment, *f*, significantly increases environmental dynamism (Column F, rows 2 and 9) *and* munificence (Column L, rows 2 and 9) only at high levels of transience, *t*, and change, *r* and *c* (P1).
2. Increased opportunity flows (*t* and *f*) significantly increase dynamism at high change levels, *r* and *c* (Column F, rows 3 and 10), but their effect on munificence (Column L, rows 3 and 10) depends on how transience is triggered (P2).
3. Increased change (*r* and *c*) significantly decreases environmental munificence (Column L, rows 6 and 13) at high flow levels (*t* and *f*), but the extent to which it increases dynamism (Column F, rows 6 and 13) depends on how transience is triggered (P3).
4. Increased opportunity flows and change significantly increase environmental dynamism (Column F, rows 7 and 15) and decrease munificence (Column L, rows 7 and 15) (P4).